


# Risk contagion of global stock markets under COVID-19: A network connectedness method

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## Abstract

COVID-19 spread throughout the world during 2020, bringing an increase in global financial risk. We use connectedness network to investigate the risk contagion among global stock markets during the COVID-19 pandemic and analyse its source. Furthermore, we use spectrum analysis to explore the risk contagion effects on different frequency bands, which allows us to explore its speed and channels. We find that the United Kingdom and Italy are core transmitters of risks, and connectedness is mainly driven by low-frequency components, which demonstrates that the risks are spread by affecting supply chains in global markets and investors' long-term expectations for the economy.

*Key words:* COVID-19; Risk contagion; Connectedness network; Spectral analysis

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## 1. Introduction

Since the outbreak of coronavirus disease 2019 (COVID-19), more than 200 countries and territories have been affected by this pandemic (Worldometers, 2020). The risks of financial crisis caused by COVID-19 are concentrated in deterioration of liquidity, credit risk contagion, unemployment and economic recession. United Nations Secretary-General António Guterres said that a global recession – perhaps of record dimensions – is a near certainty (UN, 2020).

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The chain reaction triggered by COVID-19 is complex and massive, and it has caused a new round of risk contagion among global stock markets. The United Nations Resident Coordinator Nicholas Rosellini announced that this is not just a public health crisis. This is a social crisis, a humanitarian crisis, and an economic crisis (UN, 2020). In the early stage of the COVID-19 crisis, the Chinese stock market plunged sharply in a short time, and global capital quickly fled the Asian market (CCTV, 2020). In the US stock market, the market-wide circuit breakers that attempt to prevent panic trading were triggered four times in March alone (Reuters, 2020). While the prevention of the pandemic began to improve from July to November, the US suffered the most from confirmed cases, followed by India and Brazil, which indicates a potential threat of risk from these markets (Worldometers, 2020). In this study, we consider how risk spreads among stock markets through the stock market turmoil during the COVID-19 pandemic. Which stock markets are risk issuers, and which are risk receivers? What are the characteristics of the rate of risk contagion spread and its channels? These questions are of great importance for investment portfolio construction, risk management and government regulation. From the perspective of portfolio construction, investors who tend to make long-term investments pay more attention to slower risk contagions, while investors who prefer short-term investments may focus on risks with a short propagation time. In addition, different stock markets may play different roles in the process of spreading global stock market risk contagion in different periods or cycles. Hence, policymakers and investors are advised to draw attention to this dynamic to protect against different risk shocks over different periods of time.

The common connectedness measure represents the spillover effects of rate of return or volatility among financial assets or financial markets, including the trend, path, strength and network structure of the spillover effects (Diebold and Yilmaz, 2009; 2012). The core idea is to analyse the contribution of structural shock generated by an endogenous variable in the system to the next phase prediction error of other endogenous variables. This paper focuses on using connectedness to measure the spillover effects of volatility to study the risk contagion of stock markets during COVID-19. The traditional measurement methods of correlation among financial assets focus more on the correlation between pairs of assets or between a given asset and the overall market (Diebold and Yilmaz, 2011). For example, Wang and Liu (2016) use a VAR-structural-GARCH model to find the main driver of fluctuations in Asian financial markets during both the 1997 Asian financial crisis and the 2008 global financial crisis. Škrinjarić, and Šego (2019) evaluate risk spillovers between selected CESEE (Central, Eastern and South-Eastern Europe) stock markets using the VAR model as well. However, our employment of the connectedness measure can reveal the spread of risk in the entire asset network from the perspective of the network. The connectedness measure allows us to identify the path, intensity and core issuers of risk contagion in the network

from the static perspective, and the dynamic trend of the overall risk level of the system as well as the risk contribution of individual assets can be studied from the dynamic perspective.

The global pandemic has gone through multiple stages since the outbreak of COVID-19, with China, developed countries in Europe, the United States and developing countries such as India and Brazil successively becoming pandemic centres. With the progression of the pandemic, a variety of phenomena have emerged in the global stock market. We believe that these phenomena are not always driven by a single country or market, so we hope to study the risk contagion in global financial markets during COVID-19 from a network perspective. In view of these methodological advantages and global financial market conditions during COVID-19, we adopt the Diebold and Yilmaz (2012) network connectedness method. We use variance decompositions to explore the network structure characteristics of global stock market risk contagion during COVID-19 from the static and dynamic perspectives to provide a reference for the identification and monitoring of global systemic risk contagion.

At the same time, we aim to further explore the speed and channels of risk contagion. We follow Baruník and Křehlík (2018) and separate network connectedness into high-frequency and low-frequency components to explore the short-term and medium- and long-term risk contagion effect between the global stock markets under COVID-19. The high-frequency connectedness means high-speed transmission, which corresponds to short-term risk of infection, and vice versa. In particular, when studying the risk contagion process of financial markets, we should not only pay attention to the size and direction of risk spillover but also capture the speed of risk contagion. The structural shock produced by a market will bring about a risk spillover effect, and the difference in spillover frequency and speed often indicates that the channels of risk contagion are different. Under the impact of COVID-19, factors such as the spread of panic, the transmission of various links in the supply chain of global economic activities, and the flow of capital between markets may all become channels of risk contagion among global stock markets. In the short term, due to panic sentiment, funds flow rapidly between markets, and risk contagion through this channel is fast. In the medium and long term, global economic activities and international trade will allow risks to pass through the links in the industry chain and finally be reflected in the stock market through investors' long-term economic expectations, and risk contagion through these channels is slow. Baruník and Křehlík (2018) separate risk contagion effects into short-term and medium- and long-term by separating network connectedness into high-frequency and low-frequency components. This separation helps us better identify the speed and channels of risk contagion so that regulators can more accurately formulate measures to prevent systemic risk input.

Based on the above analysis, we use network connectedness analysis methods in accordance with generalised variance decomposition and spectrum

decomposition to study the risk contagion effect of stock markets in 19 G20 countries (i.e., excluding the European Union) during the COVID-19 pandemic. We select these countries in consideration of their external financial influence and performance during COVID-19. A significant number of these countries have become epicentres of the global pandemic following the initial COVID-19 outbreak, with a large number of infection cases. Moreover, these 19 countries have relatively developed capital markets and play the most important role in global economic and financial activities. First, through static connectedness network analysis, it is found that the countries with the largest total connectedness during COVID-19 are the United Kingdom and Italy, which were more severely affected at this stage. Although China was the first country hit by a COVID-19 outbreak, its pandemic prevention measures have achieved remarkable results. Affected by COVID-19, the stock market experienced a short period of volatility. Second, through dynamic connectedness network analysis, we find that, in January 2020, while China was affected by COVID-19, China's connectedness increased dramatically, becoming the main risk issuer in the global market. In March, Japan, the US, Canada and South Africa saw significant increases in *NET* connectedness, becoming the main sources of risk contagion in global markets. The sharp increase in *NET* connectedness since May in Germany, Italy, Brazil and Australia denotes that new sources of risk appeared during this period, most importantly due to the dire economic situation in these countries. Since August when the pandemic began to improve, *NET* connectedness of developed economies returned to positive, driven by high-frequency *TO* connectedness, which means they returned to being the core source of global risk contagion. Finally, it is found that connectedness is dominated by low-frequency components during both COVID-19 and the 2008 subprime mortgage crisis in the United States. Compared to the subprime crisis, however, the value of low-frequency connectedness during COVID-19 proved greater. This indicates that investors are pessimistic about economic development in the future and, consequently, are more cautious about short-term information processing.

This paper makes the following three contributions. First, this paper adds to the existing literature on systematic risk. Previous research has focused mainly on the subprime loan crisis and the European debt crisis, while this paper is more concerned with the recent global public events surrounding the COVID-19 pandemic. Taking 19 countries from the G20 (excluding the European Union) as research objects, this paper answers the scientific question of how risk has been transmitted through stock market turmoil during the COVID-19 pandemic.

Second, technologically speaking, we use static and dynamic network connectedness methods to explore the network structure of global stock market risk contagion during the COVID-19 pandemic. From the static perspective, we explore the network characteristics of risk contagion in global stock markets. We answer the question of which stock markets are risk issuers

and which are risk receivers. From the dynamic perspective, the volatility in systemic risk during the COVID-19 pandemic is revealed. We answer the question of when connectedness experiences a steep rise and fall and what events drive this volatility.

Finally, to be more specific, we use spectrum decomposition to further explore the transmission and potential channels of risk contagion among stock markets during the COVID-19 pandemic. Spectrum decomposition helps us separate network connectedness into high-frequency and low-frequency components and better identify the transmission and channels of risk contagion, such as the spread of panic, the transmission of the shocks through various links in the supply chain of global economic activities, and the flow of capital between markets. Understanding these issues is of great importance for investment portfolio construction, risk management and government regulation.

The remainder of this paper is organised as follows. Section 2 discusses how our work is related to the existing literature. Section 3 describes our data and methodology. Section 4 presents the results of our empirical analysis. Finally, we conclude in Section 5.

## **2. Literature review**

Since the financial crisis in 2008, academic research on systemic risk has become more comprehensive, while diverse popular models and methods have emerged. Currently, the widely and sufficiently used methods include SRISK (Brownlees and Engle, 2017) and  $\Delta\text{CoVaR}$  (Adrian and Brunnermeier, 2016). These methods only measure pairwise interaction and rely on a linear Gaussian model (Diebold and Yilmaz, 2011). As the openness of financial markets in various countries has improved, the relationship between different assets and different financial institutions has been enhanced. Financial risks no longer spread linearly, and shocks can propagate across different markets. Thus, network structure analysis has attracted increasing attention, varying from academia to industry. The network connectedness model based on variance decomposition proposed by Diebold and Yilmaz (2012) aims to measure connectedness at various levels, from pairwise to system-wide. Its core idea is to analyse the structural impact of one endogenous variable in the system on the volatility change of other endogenous variables in the next period. On the one hand, this method can study the change of total connectedness from a macro perspective, and, on the other hand, it can also explore the directional network connectedness between micro subjects from a micro perspective.

Since the network connectedness model was proposed, it has been widely used by scholars. Antonakakis (2012) uses the model to analyse the volatility spillovers between the four major foreign exchanges before and after the introduction of the Euro. The conclusion shows that cross-market volatility spillovers are bidirectional, with the Euro being the sender and the British Pound being the receiver. Alter and Beyer (2014) advance the research model to

analyse the spillover relationship between the sovereign credit market and Eurozone banks during the European debt crisis, assess the direction of financial crisis transmission, and confirm that the spillover effect and the possibility of risk contagion increased during the crisis. Antonakakis *et al.* (2014) use structural decomposition to expand the network connectedness index and find that economic policy uncertainty (EPU) was an impact transmitter of shocks between 1997 and 2009. Demirer *et al.* (2018) enrich the research methods under the framework of relevance research and measure the monthly connectedness of financial entities from the perspective of principal component analysis, with the insurance industry being the research object. The results of their study show that, since 2005, the banking, securities and other industries and the insurance industry have a high level of correlation, which indicates that the systemic risks of various sub-industries in the financial industry have increased synchronously. Diebold and Yilmaz, 2016 engage in a discussion from the perspective of two major markets in Europe and America and further expanded the range of the research object of systemic risk. Based on the volatility of the European and American stock markets in the past decade, they establish a multinational network of financial institutions. Corbet *et al.* (2018) explored the volatility spillover between cryptocurrencies and other financial assets in the background of the rapid development of the digital economy, confirming that the interaction between cryptocurrencies is significant and basically not impacted by other markets. The spillover relationship between cryptocurrencies and other financial assets is not obvious.

In addition, scholars have also decomposed network connectedness into different frequencies through spectrum decomposition methods, studied connectedness on different frequency bands, and examined the driving factors and transmission channels behind connectedness. Baruník and Křehlík (2018) apply the Fourier transform to the impulse response function in the network connectedness method to separate high-frequency and low-frequency network connectedness to explore the different characteristics of network connectedness in different frequency bands. On this basis, Tiwari *et al.* (2018) conduct a study on the volatility spillover effects of four global assets: stocks, sovereign bonds, credit default swaps (CDS) and currencies. Studies have shown that, at higher frequencies, connectedness is higher, and the net connectedness of markets is different at different frequencies. Balli *et al.* (2019) study the frequency connectedness among 22 commodity uncertainty indicators and find that, during a crisis, the spillover effect of precious metals and other commodities weakens and could be used as a safe-haven asset. At the same time, it is found from the decomposition results of connectedness that the low-frequency connectedness of the commodity market is stronger. Maghyreh *et al.* (2019) apply the frequency domain decomposition method to the study of the connectedness between gold and Islamic securities and find that gold hedges the risk of Islamic bonds in the short and medium term and plays a general but stable role in hedging and dispersing Islamic stocks. Wang and Wang (2019)

study the dynamic changes in the frequency connectedness of crude oil and China's stock market volatility spillovers and find that overall volatility spillovers are driven by short-term spillovers. At the same time, China's spillover effect during the 2015 financial crisis is negative, mainly due to long-term factors.

In summary, academic research methods for systemic risk are divided into two main categories: traditional methods and network structure analysis methods. Network connectedness models based on variance decomposition and spectrum decomposition methods are gaining attention. We find that many scholars have focused their research on the subprime crisis and the European debt crisis, and it is very important to prevent systemic risks during an economic and financial crisis. Since the outbreak of COVID-19, global economic activities and financial markets have received significant impacts, but few scholars have studied the systemic risks of this period. Yang *et al.* (2020) pay attention to the impact of the pandemic on China's macroeconomic and financial markets during COVID-19. The scholars use the connectedness model proposed by Diebold and Yilmaz to study the dynamic evolution of the risk contagion relationship. The results show that domestic systemic risks tend to slow down after a rapid increase in the short term, and the domestic financial market is the impact receiver of international financial events. This paper aims to use the network connectedness model and spectrum decomposition method to study the global systemic risks and risk contagion during COVID-19 in the frequency domain and provide more specific evidence and suggestions for the administrative prevention of systemic risks during COVID-19.

### 3. Methodology

To study global stock market risk contagion during COVID-19, we use network connectedness to measure the spillover effect of volatility. In the modelling process, we take 19 G20 countries (except European Union) as research objects. Drawing on the ideas of Diebold and Yilmaz (2012), the vector autoregressive model (VAR) is first employed to describe the relationship of the mutual influence between the stock markets of 19 countries, which promotes the study of the problem of financial market risk contagion during COVID-19 as a whole. Furthermore, we use generalised variance decomposition to analyse the static and dynamic changes of risk contagion among global stock markets under COVID-19. On the one hand, it can measure the contribution of risk spillover from each financial market after the impact of external events during the pandemic. On the other hand, it can also explore the directional network connectedness between global stock markets to identify the strength and direction of risk spillovers in the stock markets. Finally, we draw on the spectrum decomposition method proposed by Baruník and Křehlík (2018) to isolate the high-frequency and low-frequency connectedness by decomposing the speed of risk contagion and explore the short-term and

medium- and long-term risk contagion effects of the global stock market under COVID-19 to analyse the speed and channels of global stock market risk contagion. The following is a detailed description of the method.

### 3.1. Network connectedness method based on generalised variance decomposition

Drawing on the ideas of Diebold and Yilmaz (2012), we first consider constructing a vector autoregressive model (VAR), which can effectively estimate the dynamic relationship between the 19 stock markets, avoiding modelling each individual financial market separately. Next, we use the generalised variance decomposition method to measure the contribution of each financial market risk spillover after the structural shock occurred during the epidemic and study the dynamic risk contagion among financial markets.

The VAR model takes each endogenous variable in the system as a function of the lagged values of the endogenous variables in the system. A VAR model with  $n$  variables and  $p$  lags is defined in the following form:

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \cdots + \Phi_p x_{t-p} + \varepsilon_t, \varepsilon_t \sim (0, \Sigma) \quad (1)$$

where  $x_t$  is an  $n \times 1$  vector of endogenous variables at time  $t$  and  $p$  is the lag order.  $\Phi_1, \dots, \Phi_p$  are the  $N \times N$  coefficient matrices to be estimated. Note that the  $N \times N$  matrix lag polynomial is  $\Phi(L) = [I_N - \Phi_1 L - \cdots - \Phi_p L^p]$ , and so Equation (1) can be written as  $\Phi(L)x_t = \varepsilon_t$ . If the roots of  $\det|\Phi(L)|$  are outside the unit circle, then Equation (1) satisfies the stability condition, which can be expressed in infinite-order vector moving average form:

$$x_t = \Psi(L)\varepsilon_t \quad (2)$$

where  $\Phi(L) = [\Psi(L)]^{-1}$ .

Furthermore, we can deduce the generalised forecast error variance decomposition (GFEVD):

$$\theta_{j,k}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^H (\Psi_h \Sigma)^2_{j,k}}{\sum_{h=0}^H (\Psi_h \Sigma \Psi_h^T)_{j,j}} \quad (3)$$

where  $\Psi_h$  is a matrix of moving average coefficients with lag  $h$  defined above and  $\sigma_{kk} = (\Sigma)_{k,k}$ .  $\theta_{j,k}^H$  defines the shock contribution of the  $k$ th financial market to the forecast error variance of the  $j$ th financial market at horizon  $H$ . Because  $\sum_{k=1}^N \theta_{j,k}^H \neq 1$ , we normalise the elements in the matrix:

$$\tilde{\theta}_{j,k}^H = \theta_{j,k}^H / \sum_{k=1}^N \theta_{j,k}^H \quad (4)$$

According to the definition,  $\theta_{j,k}^{\tilde{H}}$  measures the pairwise connectedness from market  $k$  to market  $j$  at horizon  $H$ . Then, we can aggregate information to measure total connectedness and directional connectedness. The total connectedness,  $TOTAL$ , is defined as:

$$TOTAL = 100 \times \frac{\sum_{j \neq k} \theta_{j,k}^{\tilde{H}}}{\sum \theta^{\tilde{H}}} \quad (5)$$

Based on the above analysis, we can create the connectedness table shown in Table A1. The  $N \times N$  submatrix in the upper left corner represents the directional network connectedness between  $N$  markets, and the element in the  $i$ th row and  $j$ th column is the volatility spillover effect from the  $j$ th market to the  $i$ th market, that is, the percentage contribution of the  $j$ th market to the variance in the forecast error of the  $i$ th market, which indicates the size of the risk contagion from the  $j$ th market to the  $i$ th market. The  $i$ th element in the column 'FROM connectedness' is the volatility spillover effect from the other  $(N - 1)$  markets to the  $i$ th market, which represents the size of the risk contagion from the other  $(N - 1)$  markets to the  $i$ th market. The  $j$ th element in the row 'TO connectedness' is the volatility spillover effect from the  $j$ th market to the other  $(N - 1)$  markets, which represents the size of the risk contagion from the  $j$ th market to the other  $(N - 1)$  markets. The  $j$ th element of the 'NET connectedness' row is the connectedness from the  $j$ th market to the other  $(N - 1)$  markets minus the connectedness of the other  $(N - 1)$  markets to the  $j$ th market, which represents the net value of risk contagion from the  $j$ th market. The lower right corner of the table is the total connectedness,  $TOTAL$ , defined by Equation (5).

### 3.2. Network connectedness method based on spectrum decomposition

Next, we use the method of Baruník and Křehlík (2018) to study the transmission and channels of global stock market risk contagion during COVID-19 through spectrum decomposition. Specifically, we separate the connectedness into high-frequency and low-frequency connectedness through frequency-domain decomposition, where high-frequency connectedness represents the short-term risk contagion in the flow of funds and investor sentiment and low-frequency connectedness represents the risk contagion in the medium and long term through channels such as global supply chains and investors' medium- and long-term expected economic results.

We define the Fourier transform of the impulse response  $\Psi_h$  in the generalised variance decomposition:

$$\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h \quad (6)$$

The principle of the Fourier transform is to use the sum of a series of trigonometric functions to approximate a periodic signal and then express this set of time-varying time-domain signals as a set of discrete points in the frequency domain, thereby transforming the signal from the time domain to the frequency domain. In the study of the risk contagion process, we pay attention to not only its size and direction but also its speed. A high-risk contagion speed means a short propagation time, which corresponds to a higher frequency, and vice versa. Therefore, the Fourier transform helps us project the risk contagion in financial markets onto different frequency bands and obtain connectedness at different frequencies to analyse the different speeds and channels of risk contagion.

Furthermore, we obtain the generalised causation spectrum via spectrum decomposition at a specific frequency  $\omega \in (-\pi, \pi)$ :

$$(f(\omega))_{ij} = \frac{\sigma_{jj}^{-1}(\Psi(e^{-i\omega})\Sigma)_{i,j}^2}{(\Psi(e^{-i\omega})\Sigma\Psi^T(e^{+i\omega}))_{i,i}} \quad (7)$$

where  $(f(\omega))_{ij}$  represents the part of the  $i$ th variable's frequency spectrum that is impacted by the  $j$ th variable at a given frequency  $\omega$ , that is, the part of the  $i$ th financial market's spectrum that is infected with the risk contagion of the  $j$ th financial market at a particular speed. The quantity is a within-frequency causation, as the denominator represents the whole spectrum of the  $i$ th market at frequency  $\omega$ . To obtain a natural decomposition of the original GFEVD in the frequency domain, we can weight  $(f(\omega))_{ij}$  by the frequency weight of the  $i$ th variable, which is calculated by the weight formula  $\Gamma_i(\omega)$ :

$$\Gamma_i(\omega) = \frac{(\Psi(e^{-i\omega})\Sigma\Psi^T(e^{+i\omega}))_{i,i}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} (\Psi(e^{-i\lambda})\Sigma\Psi^T(e^{+i\lambda}))_{i,i} d\lambda} \quad (8)$$

where  $\Gamma_i(\omega)$  represents the power of the  $i$ th variable at frequency  $\omega \in (-\pi, \pi)$ , and  $\omega$  sums over the frequencies to a constant value of  $2\pi$ . Then, let us suppose we have a frequency band  $h = (a, b) : a, b \in (-\pi, \pi)$ ; we can use the generalised causation spectrum  $(f(\omega))_{ij}$  and its weight formula  $\Gamma_i(\omega)$  to obtain the GFEVD for frequency band  $h$ :

$$\theta_{ij}^h = \frac{1}{2\pi} \int_a^b \Gamma_i(\omega) (f(\omega))_{i,j} d\omega \quad (9)$$

As we can see, if we have  $h \rightarrow H = (-\pi, \pi)$ , then we can define the following formula:

$$\theta_{ij}^H = \frac{1}{2\pi} \int_{-\pi}^{\pi} \Gamma_i(\omega) (f(\omega))_{i,j} d\omega \quad (10)$$

$\theta_{ij}^H$  can be viewed as the weighted average of the generalised causation spectrum  $(f(\omega))_{ij}$ , and it reconstructs the original GFEVD in the time domain calculated by Equation (3). Based on Equations (9) and (10), we normalise the generalised variance decompositions over frequency band  $h$  to obtain Equation (11). Similar to the time domain, this is a measure of the pairwise connectedness from market  $j$  to market  $i$  over frequency band  $h$ , and we can calculate the total connectedness and directional connectedness over frequency band  $h$ :

$$\tilde{\theta}_{ij}^h = \frac{\theta_{ij}^h}{\sum_j \theta_{ij}^H} \quad (11)$$

$$TOTAL^h = 100 \times \frac{\sum_{j \neq k} \tilde{\theta}_{j,k}^h}{\sum \tilde{\theta}^H} \quad (12)$$

The above equation is used to calculate the numerical values we finally present in the connectedness table. We can separate network connectedness into two frequency bands, high frequency and low frequency, by setting the upper and lower limits of the spectral band  $h = (a, b)$  to obtain the connectedness from financial market  $j$  to financial market  $i$  over a specific frequency band. The generalised spectral integration of the high-frequency band can achieve volatility connectedness in a short period of time, which represents the short-term risk contagion reflected in capital flows and investor sentiment. The generalised spectral integration in the low-frequency band can achieve volatility connectedness that can only be spread across the medium and long terms, which represents that mid- and long-term risk contagion is reflected through global supply chains and investors' mid- and long-term expectations of economic results.

### 3.3. Data description

The existing literature uses volatility to measure market risks (Diebold and Yilmaz, 2011). We also examine the spread of systemic financial risks from the perspective of market volatility spillovers. The research objects of this paper are mainly stock indexes of 19 countries (US: the United States, CN: China, JP: Japan, DE: Germany, IN: India, GB: United Kingdom, FR: France, IT: Italy, BR: Brazil, CA: Canada, KR: South Korea, RU: Russia, AU: Australia, MX: Mexico, ID: Indonesia, SA: Saudi Arabia, TR: Turkey, AR: Argentina, ZA: South Africa). The sample interval is from 31 December 2019 to 30 November 2020. The date 31 December 2019 is when Wuhan Municipal Health Commission first gave notification of the unknown pneumonia pandemic situation, and we believe that is the earliest date for the market to learn about this pandemic. The data comes from the Bloomberg database. We refer to

Alizadeh et al. (2002) to construct the daily volatility of assets through the highest price, lowest price, opening price and closing price of an asset. The formula is as follows:

$$\hat{\sigma}_{gk}^2 = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2 \quad (13)$$

where  $h$ ,  $l$ ,  $o$  and  $c$  represent the natural logarithm of the daily highest price, lowest price, opening price and closing price of 19 assets, respectively.

The descriptive statistics of the daily volatility of the 19 stock markets during COVID-19 are shown in Table A2. From the mean value of volatility, Saudi Arabia's stock market has the lowest volatility during COVID-19, while Argentina, Brazil, Russia and Italy have higher volatility among the 19 countries. From the extreme values of volatility, the maximum volatility in Brazil, India and Italy is relatively high. Based on this, we can find that emerging markets tend to be more volatile. Among developed markets, countries with relatively severe pandemics during the sample period are more volatile. Of the developed countries in the G20, Italy, with the highest volatility, witnessed a great outbreak of COVID-9 in March 2020.

## 4. Empirical results

### 4.1. Static connectedness analysis during COVID-19

First, based on the network connectedness method proposed by Diebold and Yilmaz (2012), we analyse the risk spillover effects between countries during COVID-19. We conduct static connectedness analysis on the sample interval and use the network graph to more clearly show the path, intensity and core sender of the systemic risk infection. The sample interval is from 31 December 2019 to 30 November 2020. Starting from the first notification of the pandemic situation by Wuhan Municipal Health Commission, the sample interval includes as much sample information as possible. Due to the small sample size during COVID-19, we use the stationary bootstrap method proposed by Politis and Romano (1994) for the significance test of the data in the connectedness table. Multiple random-length block samples are spliced into new samples to achieve the purpose of expanding the sample, and the length of each block is uniformly distributed. In this paper, we use the resampling technique to obtain a sample with a length of 3,000 to calculate the connectedness, repeat the above sampling process 5,000 times, and calculate the distributed  $t$ -value. The total connectedness performance and the total connectedness network of the 19 sample countries are shown in Table A3 and Figure A1, respectively.

By observing the table and graph of total connectedness during COVID-19, we find that, during this period, the core senders of risk are the United

Kingdom and Italy, reaching 146.95 percent and 141.55 percent, respectively. Germany and Brazil also have larger *TO* connectedness. From the perspective of fluctuation reception, the *FROM* connectedness of the 19 countries is between 44.55 percent and 86.53 percent, and the difference among countries is relatively small. Although China was the first country to experience an outbreak of COVID-19, the pandemic prevention measures have achieved remarkable results. As a result of these measures, the stock market returned to stability after a short period of volatility. Taking into account the degree of market openness, China has the lowest *TO* connectedness in the sample, and the *NET* connectedness is negative, presenting net fluctuation reception status. For the United Kingdom, its economy has been affected by the impact of COVID-19 and has experienced an unprecedented recession. According to statistics from the UK Statistics Office, in the first quarter of this year, gross domestic product (GDP) shrank by 2 percent from the previous quarter, the largest quarterly decline since the fourth quarter of 2008. Especially in March, GDP fell by 5.8 percent month-on-month. In addition, the Brexit transition period was due to end at the end of 2020. All of these lead the United Kingdom to become a major risk sender during the pandemic.

Second, we draw on the method of Baruník and Křehlík (2018) to convert the connectedness during COVID-19 through Fourier transformation into high- and low-frequency sub-bands. Connectedness represents the contribution of the shock generated by the fluctuation of market *i* to the next period of fluctuation of market *j*, and the high frequency and low frequency of connectedness indicate the speed of the risk propagation. Among them, high frequency represents short-term connectedness of 0–5 days, indicating the risk of being able to spread within 5 days; low frequency represents mid- to long-term connectedness of more than 5 days, indicating that it takes more than 5 days to spread the risk. We study the speed and influence cycle of different risk contagion during the pandemic through the connectedness of sub-bands to obtain the contagion channel behind it and provide suggestions for risk prevention. The high- and low-frequency connectedness performance of the 19 sample countries are shown in Tables A4 and A5, respectively. Figure A1 shows the sub-band connectedness network between the 19 sample countries.

Through observation of the sub-band connectedness, we find that the low-frequency *FROM* connectedness of the 19 countries is overall larger and less varied, while the low-frequency *TO* connectedness is obviously different, mainly concentrating in the United Kingdom and Italy, reaching 119.68 percent and 116.32 percent, respectively. For short-term risk contagion, we find that high-frequency *TO* connectedness is relatively consistent, mostly approximately 22 percent, and high-frequency *FROM* connectedness varies among countries. It is worth noting that the developed countries, such as the United States, Japan and Germany, have significantly larger low-frequency *TO* connectedness than high-frequency *TO* connectedness during COVID-19.

China's *TO* connectedness in both frequency bands is low and China is mainly a risk receiver.

The results show that the connectedness during the pandemic is driven mainly by low frequencies. We believe this stems from two aspects. On one hand, the suspension of production in countries during the pandemic led to a decline in demand, and the risk was passed between global stock markets through fundamental channels such as international trade and foreign direct investment (FDI); on the other hand, COVID-19 led to a general downward trend in global economic fundamentals, which triggered a high degree of uncertainty in the economic and financial system. With panic in the entire financial market, investors showed lower expectations for economic fundamentals. The lower expectation will last for a long time, until the end of COVID-19. Compared with the period of economic stability, the impact of uncertainty shocks in the system during turbulent times is significant and long-lasting, so it appears as a driving force for low-frequency connectedness to increase total connectedness. In terms of medium- and long-term risk transmission, the United Kingdom and Italy have the strongest *TO* connectedness and *NET* connectedness, indicating that they are the senders of low-frequency risk transmission. A possible explanation may be that the relatively slow pace of response measures has led investors to be more pessimistic about the future expectations of their fundamentals.

The high-frequency connectedness is mainly due to the short-term changes in investor sentiment caused by capital flow factors and the impact of short-term events, which does not dominate during COVID-19. The risk contagion of the stock market is more from the downside of fundamentals and the low expectations of investors. In the high-frequency connectedness network structure, Saudi Arabia and France have the highest *TO* connectedness and *NET* connectedness, indicating that they are the senders of short-term risk contagion due to emergencies. At the same time, *TO* connectedness and *NET* connectedness in the United Kingdom and Russia are also larger. This may be due to the short-term investor sentiment caused by the stock market crashes in the two countries and the phenomenon of safe investment transfer of international hot money to reduce the proportion of positions in global equity assets.

#### 4.2. Dynamic connectedness analysis during COVID-19

Based on the static analysis of the entire sample, we analyse the dynamic evolution of risk contagion during COVID-19. We first calculate the total connectedness of the stock markets of the 19 countries and draw a dynamic graph of total connectedness to analyse its fluctuations. For comparison with the situation during the non-COVID-19 period, we set the sample interval from 1 July 2019 to 30 November 2020. The graph of total connectedness dynamics is shown in Figure A2(a).

As shown in Figure A2(a), the total connectedness of the global stock markets was relatively stable throughout 2019, fluctuating between 78 percent and 85 percent. However, since January 2020, connectedness has risen sharply, the risk contagion effect of various markets has increased significantly, and global systemic risks have increased rapidly. With the rapid outbreak of COVID-19, Wuhan announced the closure of the city due to COVID-19 on 23 January 2020. Under the impact of this event, the global total connectedness increased sharply from 80.0 percent to 85.5 percent in the following trading day, reaching a peak, and systemic risks spread rapidly around the world. Subsequently, with the gradual control of COVID-19 in Mainland China and steady progress in the resumption of work and production, total connectedness fell briefly as the market digested the impact of COVID-19. However, since late February, with the rapid spread and gradual outbreak of COVID-19 around the world, the effect of risk contagion increased again. Affected by the Italian pandemic and the crude oil price war between Saudi Arabia and Russia, the global stock market dropped sharply, and the total connectedness once again reached a high point on 12 March, reaching 88.8 percent. In the next two months, COVID-19 continued to deteriorate worldwide, and total connectedness continued to rise. On 22 May 22, *The Lancet* published the results of the world's first human trial of a COVID-19 vaccine, showing that the vaccine is safe, well tolerated, and can induce an immune response against COVID-19 in the human body. Due to this good news, global total connectedness fell from 89.8 percent to 85.9 percent over the following days. On 20 July, *The Lancet* released the latest results of two COVID-19 vaccine I/II clinical trials, both of which can generate an immune response to the coronavirus (SARS-CoV-2) and can induce a highly effective T-cell immune response. Adding the impact of the EU's agreement on a €750 billion recovery fund on 21 July to the effects of the *The Lancet's* report, global total connectedness has fallen sharply since then, from 87.2 percent to 80.3 percent. Since August, the growth rate in the number of new cases of COVID-19 worldwide has been slowing. In addition, economic data from many countries, including the United States, have been better than expected. As a result, total connectedness has remained relatively stable.

The total connectedness reveals how systemic risk fluctuates during COVID-19, but it does not reveal what type of financial cycle this fluctuation comes from. We cannot tell whether the risk contagion between global markets comes from long-term changes in global economic activity under the impact of the pandemic or short-term changes in asset prices brought about by financial activities. Finding the source of risk is essential for policymakers and investors to prevent risks. Therefore, we refer to the method of Baruník and Křehlík (2018) to decompose the total connectedness into high-frequency and low-frequency bands, corresponding to short-term (1–5 trading days) and medium- and long-term (more than 5 trading days) risk, respectively. Figure A2(b) shows the spectral decomposition of total connectedness.

Comparing the fluctuation trend of connectedness in the two frequency bands with the total connectedness fluctuation trend, we get a significant rule that, during COVID-19, the increase in total connectedness is driven mainly by low-frequency components, which is consistent with our conclusion in the static connectedness analysis. During 2019, total connectedness was driven by high frequency. Low-frequency connectedness rapidly rose to exceed high-frequency connectedness in March 2020 and remained at a high level. In July 2020, benefiting from the improvement in the pandemic, low-frequency connectedness gradually declined and returned to less than high-frequency connectedness by the end of the month. We attribute this to the general downturn in the global economic fundamentals caused by COVID-19 and the lower expectations that investors had for economic fundamentals. In the context of economic activity and supply chain globalisation, with the outbreak and deterioration of the new crown pandemic, the order of economic activities in various countries has been greatly disrupted and gradually spread to trade activities. With the continuous spillover of risks, the formation of global economic fundamentals has generally declined, triggering a sharp increase in risk contagion in the medium and long term. The high-frequency band connectedness is mainly due to global capital flow factors and short-term event shocks caused by investors' short-term emotional changes, which did not dominate during COVID-19.

Based on the dynamic analysis of total connectedness and connectedness on frequency bands of global stock markets, we conduct a detailed analysis of the dynamic connectedness of the stock markets of 19 countries and examine the risk contagion effects of various countries and regions. First, we study the changes in the *NET* connectedness of various markets over time. Figure A3 shows the *NET* connectedness dynamics of each country.<sup>1</sup>

*NET* connectedness measures the difference between issued and received connectedness in a segment, reflecting the net effect of risk contagion between one market and others. Positive *NET* connectedness means that the market outputs fluctuation to other markets, while negative *NET* connectedness means that the market receives fluctuation from other markets. We find that, during 2019, the United States, the United Kingdom, the European Union countries, Canada and Australia, as traditional developed economies with mature financial market systems, maintain positive *NET* connectedness for a long time and consequently impact other global markets. They are the core sources of global risk contagion. At the same time, the *NET* connectedness of BRICS countries such as China, and other developing countries has been negative for a long time, and they are the major receivers of global risk contagion. During

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<sup>1</sup>To simplify the image, we only included dynamic *NET* connectedness for 9 typical countries (including US: the United States, CN: China, DE: Germany, GB: United Kingdom, IT: Italy, BR: Brazil, CA: Canada, RU: Russia, AU: Australia) in Figure 3 in Appendix I, the figures of dynamic connectedness of all countries are put in Figure 6 in Appendix II.

COVID-19, *NET* connectedness of stock markets in all countries has fluctuated significantly. In January 2020, while China was affected by COVID-19, China's *NET* connectedness increased dramatically, becoming the main risk issuer in the global market. Subsequently, with the improvement in the pandemic in China, China's *NET* connectedness gradually declined and turned negative again in late March, re-emerging as a net receiver of risk contagion. In March, Japan, the US, Canada and South Africa saw significant increases in *NET* connectedness, becoming the main sources of risk contagion in global markets. The sharp increase in *NET* connectedness in May in Germany, Italy, Brazil and Australia means they were new sources of risk during this period, largely due to the dire economic situation in both countries. The UK and Russia became the main sources of risk contagion in global markets from late June to July. Since August, when the pandemic began to improve, *NET* connectedness of developed economies has returned to positive, which means they returned to being the core sources of global risk contagion.

*NET* connectedness analysis is used to preliminarily determine the net effect of risk contagion among various financial market segments, but the direction and speed of interaction between different markets requires further analysis using connectedness on frequency bands. We draw dynamic graphs of issuing connectedness (*TO* connectedness) and receiving connectedness (*FROM* connectedness) in the stock markets of 19 countries, as shown in Figure A4.<sup>2</sup> We analyse whether changes in *NET* connectedness are driven mainly by issuing connectedness or receiving connectedness and what type of financial cycle this connectedness comes from.

*TO* connectedness measures the volatility spillover issued by a single market to all other markets, while *FROM* connectedness reflects the volatility spillovers received by a single market from all other markets. We find that, from January to July, the increase in *NET* connectedness of each country came from the substantial increase in *TO* connectedness, and the improvement was driven by low-frequency components, which were mainly due to the impact of COVID-19 on economic activity in these countries. While they were affected by the pandemic, their economic development was temporarily stalled, and economic and financial turmoil gradually developed in the global environment. In contrast, the rise in developed economies' *NET* connectedness since August was driven by high-frequency *TO* connectedness, mainly because risk contagion returned to being caused by global capital flow factors and short-term event shocks under the situation of the improvement in the pandemic and global economy. The *FROM* connectedness shows that, from 2019 to January 2020, the global stock market

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<sup>2</sup>To simplify the image, we only included dynamic *To* and *From* connectedness for nine typical countries (US: the United States, CN: China, DE: Germany, GB: United Kingdom, IT: Italy, BR: Brazil, CA: Canada, RU: Russia, AU: Australia) in Figure A4 in Appendix I; the figures of dynamic connectedness of all countries are included in Figures A7 and A8 in Appendix II.

*FROM* connectedness was driven mainly by high-frequency connectedness, which indicates that, during this period, investors' long-term expectations of economic fundamentals did not change significantly. During this period, the impact of uncertainty in the system was quickly received and reacted to by investors, and it quickly spread in the system, forming a short-term impact. This short-term impact has become the dominant factor in the spread of systemic risk during periods of economic stability, and in this case, the total connectedness, that is, the risk of systemic risk, is low. However, with the outbreak and deterioration of COVID-19, global economic activities have been impacted, and the *FROM* connectedness of stock markets in various countries has gradually changed to be driven by low-frequency components, which also reflects the huge impact of COVID-19 on the global economy.

#### 4.3. Comparison to the 2008 US subprime mortgage crisis

In the previous section, the data samples during COVID-19 were intercepted to analyse the connectedness performance of the stock markets in various countries at that stage, that is, the channel, intensity and core sender of risk contagion. We have found that the United Kingdom, Italy and Germany became the main source of risk contagion during COVID-19, and low-frequency connectedness became the main driver of total connectedness. Similar to the global COVID-19 pandemic in 2020, the global economic recession caused by the subprime mortgage crisis in 2008 had a huge impact on global stock markets, and risk contagion also occurred among the stock markets of various countries. We intercept the data samples during the subprime mortgage crisis from August 2007 to March 2009 for network connectedness analysis and show the channel and intensity of systemic risk contagion through network diagrams more clearly. We use the method of Diebold and Yilmaz (2012) to study the total connectedness of the global stock market firstly and then use the method of Baruník and Křehlík (2018) to analyse the difference between high-frequency and low-frequency connectedness by frequency band. Also, during the analysis, we compare risk contagion during the COVID-19 period.

Based on the total connectedness results (as shown in Table A6) and the total connectedness network graph (as shown in Figure A5) of the samples during the subprime crisis, we focus mainly on the total *NET* connectedness of the global stock market. The Canada, United States and Mexico are main senders of risk contagion with a *NET* connectedness of more than 40 percent. This shows that the financial risks generated by these markets have spread to other markets along the network while Australia, China and Korea are main receivers of risk contagion with *NET* connectedness below -30 percent. Australia, in particular, was heavily affected by countries led by Canada and the United States during this period. During the subprime mortgage crisis, China's financial openness was still at a relatively low level, so both *TO* connectedness and *FROM* connectedness were the lowest values in the sample

countries. Countries such as France and Germany had a low net effect of risk contagion, so they were less affected by external markets.

Unlike the global stock market volatility risk contagion caused by COVID-19, the global stock market risk contagion caused by the subprime mortgage crisis was relatively small in terms of connectedness; the *NET* connectedness during that crisis varied from -40.69 percent to 52.92 percent while the *NET* connectedness during COVID-19 has ranged from -49.10 percent to 64.86 percent. In addition, during COVID-19, there was a phenomenon of gathering of senders with a larger number of receivers and fewer senders of risk contagion, while the numbers of senders and receivers of risk contagion are more equivalent during the subprime mortgage crisis. Looking at the global stock market during the financial crisis, developed countries were more likely to act as senders of risk contagion and developing countries were acting as receivers of risk contagion, while China's participation in global stock market risk contagion was very low.

Next, we use Fourier transformation to decompose the total connectedness by frequency band to obtain the characteristics of risk contagion in different frequency bands. The connectedness results of the sub-bands are shown in Tables A7 and A8, and at the same time, we present the corresponding connectedness network diagram (as shown in Figure A5).

Comparing the connectedness results in Tables A7 and A8 and combining the two connectedness network diagrams, it can be found that, during the subprime crisis, due to the damage to the fundamentals of the global economy, investors and policymakers were pessimistic about future economic development and at the same time more cautious about short-term information processing so total connectedness was driven mainly by low-frequency connectedness. From the high-frequency connectedness table, Germany, the European centre, had the highest *TO* connectedness and *NET* connectedness. It had a short-term impact on other global stock markets and was the main source of short-term risk contagion. In the high-frequency part, the United Kingdom had been hit by the greatest risk contagion. Short-term fluctuations had a huge impact on the British stock market. The *TO* and *NET* connectedness of China's stock market in the high-frequency band was still low among sample countries and its role in the risk contagion of the global stock market was a receiver. In terms of low-frequency connectedness, the US stock market and Canadian stock market had the highest *TO* connectedness and *NET* connectedness, which had a long-term impact on global economic fundamentals and investor sentiment. In contrast, due to the late start and low degree of openness, the *TO* and *FROM* connectedness of the Chinese stock market were the lowest among sample countries and the *TO* connectedness was only 1.54 percent.

Compared with the global stock market fluctuation caused by COVID-19, the global stock market risk contagion caused by the subprime mortgage crisis has some distinct characteristics. At the level of short-term risk contagion, the ranges of connectedness values of the two global stock market fluctuations are similar, and the fluctuations show similarities. This type of risk contagion caused by real-time information transmission and rapid capital flow along the

network has affected the global stock market by bringing short-term impact and quickly manifested as a short-term stock market linkage reaction. At the level of mid- to long-term risk contagion, the global stock market connectedness during the subprime mortgage crisis has a relatively larger value. This reflects that the risk contagion during the subprime mortgage crisis is more intense, and investors are more pessimistic about the future medium- and long-term economic development. In addition, in the process of comparative analysis of low-frequency connectedness, we find a clear transfer of risk contagion sources. During the subprime crisis, Canada and United States were the main sources of risk contagion, and during COVID-19, the United Kingdom and Italy have been the main sources of risk contagion, which was affected mainly by the direct causes of global stock market fluctuations.

We believe that similarly to the global stock market risk contagion caused by the subprime mortgage crisis, the global stock market risk contagion caused by COVID-19 was also driven mainly by low-frequency connectedness. The impact of global supply chains and mid- and long-term economic expectations on the stock market was more influential. When it comes to *TOTAL* connectedness, the latest global stock market risk contagion is more intense, and the interaction between global stock markets is more obvious, which is also consistent with the acceleration of financial globalisation. In addition, the source of this global stock market risk contagion is different from the risk contagion source during the subprime mortgage crisis, changing from the United States to the United Kingdom and Italy. This is because the United States is the source of the subprime mortgage crisis, while the other two countries' economies have suffered greatly from the COVID-19 pandemic.

Last but not least, we present the figures of dynamic *NET* connectedness of all countries in Figure A6 in Appendix II, which is a full analysis of Figure A3. We also present the figures of *TO* and *FROM* dynamic connectedness of all countries in Figures A7 and A8 in Appendix II. All the results are consistent with Figures A3 and A4.

## 5. Conclusion

In this work, we use network connectedness as a measure of the spillover effect of volatility to study global stock market risk contagion during COVID-19 to identify the size, direction, path and changes of risk contagion from both static and dynamic perspectives. We take 19 of the G20 countries as research objects. In the sample interval of COVID-19 studied in this paper, the countries with the largest total connectedness are the United Kingdom and Italy. For this stage, the countries' economies are seriously affected by the pandemic. Although China was the first country to suffer a COVID-19 outbreak, the prevention measures have achieved significant results. Affected by the pandemic, the stock market returned to stability after a short period of volatility, so the lowest connectedness in the sample was sent, and the *NET* connectedness was negative, showing a net

receiving state. Through spectrum decomposition, we find that the connectedness during the pandemic was driven mainly by low frequency. On one hand, due to the downturn in demand during the pandemic, risks infect through international trade and FDI and other fundamental channels among global stock markets. On the other hand, global economic fundamentals are generally down, and investors are showing lower expectations for economic fundamentals. The lower expectation will last for a long time, until the end of COVID-19. In terms of high-frequency connectedness, Saudi Arabia and France have larger *TO* connectedness and *NET* connectedness, which may be due to the short-term investor sentiment contagion caused by the stock market crash in the two countries and the safe investment transfer of international hot money.

Dynamic connectedness reveals the volatility of systemic risks during COVID-19. Global total connectedness began to rise sharply in January 2020, and the risk spillover effects of various markets have increased significantly. Moreover, this sharp rise is driven by low-frequency components, which is consistent with our conclusion in the analysis of static components. We attribute this to the general downturn in the global economic fundamentals caused by COVID-19 and the lower expectations that investors have for economic fundamentals. We find that, in January 2020, affected by COVID-19, China's connectedness increased dramatically, becoming the main risk issuer in the global market. Subsequently, with the improvement in the pandemic in China, China's *NET* connectedness gradually declined and turned negative again in late March, re-emerging as a net receiver of risk contagion. In March, Japan, the US, Canada and South Africa saw significant increases in *NET* connectedness, becoming the main sources of risk contagion in global markets. The sharp increase in *NET* connectedness in May in Germany, Italy, Brazil and Australia means they were new sources of risk during this period, largely due to the dire economic situation in those countries. Since August, when the pandemic began to improve, *NET* connectedness of developed economies returned to positive, driven by high-frequency *TO* connectedness, which means they returned to being the core source of global risk contagion.

Compared with the period of the subprime mortgage crisis, the stock market connectedness during COVID-19 was concentrated in the United Kingdom and Italy, while Canada and United States were the main sources of fluctuation during the financial crisis. During COVID-19, the level of volatility spillover in the global stock market was larger, indicating that the risk spread of the global market during the pandemic was more severe. Furthermore, we divide the connectedness during the subprime mortgage crisis into two high- and low-frequency bands and find that the low-frequency connectedness during COVID-19 and the subprime mortgage crisis both dominated low frequency, and the low-frequency connectedness value during the subprime mortgage crisis was bigger. Low frequency domination indicates that investors and policymakers are pessimistic about economic development in the future and, at the same time, are more cautious about economic information processing, so the total connectedness is driven mainly by

low-frequency connectedness. At the level of high-frequency connectedness, the range of connectedness values for two global stock market fluctuations is similar. This type of risk propagation caused by real-time information transmission and rapid capital flow along the network has a short-term impact on the global stock market, but high-frequency connectedness was not the main driver of global stock market connectedness, either in the COVID-19 pandemic period or in the subprime mortgage crisis.

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## Appendix I

Table A1  
Connectedness table

	$x_1$	$x_2$	...	$x_N$	FROM connectedness
$x_1$	$\theta_{1,1}^H$	$\theta_{1,2}^H$	...	$\theta_{1,N}^H$	$\sum_{j=1}^N \theta_{1,j}^H, j \neq 1$
$x_2$	$\theta_{2,1}^H$	$\theta_{2,2}^H$	...	$\theta_{2,N}^H$	$\sum_{j=1}^N \theta_{2,j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
$x_N$	$\theta_{N,1}^H$	$\theta_{N,2}^H$	...	$\theta_{N,N}^H$	$\sum_{j=1}^N \theta_{N,j}^H, j \neq N$
TO connectedness	$\sum_{i=1}^N \theta_{i,1}^H, i \neq 1$	$\sum_{i=1}^N \theta_{i,2}^H, i \neq 2$	...	$\sum_{i=1}^N \theta_{i,N}^H, i \neq N$	
NET connectedness	$TO_1 - FROM_1$	$TO_2 - FROM_2$	...	$TO_i - FROM_i$	TOTAL

This table reports the connectedness network. The  $N \times N$  sub-matrix in the upper left corner represents the directional network connectedness between  $N$  markets, and the element in the  $i$ th row and  $j$ th column is the volatility spillover effect from the  $j$ th market to the  $i$ th market, that is, the percentage contribution of the  $j$ th market to the variance of the forecast error of the  $i$ th market, which indicates the size of the risk contagion from the  $j$ th market to the  $i$ th market. The  $i$ th element in the column ‘FROM connectedness’ is the volatility spillover effect from the other  $(N - 1)$  markets to the  $i$ th market, which represents the size of the risk contagion of the other  $(N - 1)$  markets to the  $i$ th market. The  $j$ th element in the row ‘TO connectedness’ is the volatility spillover effect from the  $j$ th market to the other  $(N - 1)$  markets, which represents the size of the risk contagion of the  $j$ th market to the other  $(N - 1)$  markets. The  $j$ th element of the ‘NET connectedness’ row is the connectedness from the  $j$ th market to the other  $(N - 1)$  markets minus the connectedness from the other  $(N - 1)$  markets to the  $j$ th market, which represents the net value of risk contagion from the  $j$ th market. The bottom right corner of the table is the total connectedness *TOTAL* defined by Equation (5).

Table A2  
Descriptive statistics of volatility of the stock markets of 19 countries during COVID-19

	Number	Minimum	Maximum	Mean	Standard deviation
US	232	0.0016	0.0510	0.0105	0.0086
CN	232	0.0024	0.0283	0.0083	0.0043
JP	232	0.0000	0.0548	0.0084	0.0071
DE	232	0.0025	0.0666	0.0121	0.0092
IN	232	0.0028	0.1054	0.0115	0.0106
GB	232	0.0026	0.0594	0.0120	0.0087
FR	232	0.0019	0.0617	0.0122	0.0088
IT	232	0.0032	0.1008	0.0134	0.0107
BR	232	0.0039	0.1173	0.0168	0.0149
CA	232	0.0013	0.0613	0.0089	0.0094
KR	232	0.0036	0.0526	0.0101	0.0068
RU	232	0.0039	0.0741	0.0154	0.0111
AU	232	0.0017	0.0843	0.0101	0.0095
MX	232	0.0032	0.0584	0.0104	0.0066
ID	232	0.0017	0.0540	0.0097	0.0079
SA	232	0.0015	0.0403	0.0068	0.0055
TR	232	0.0032	0.0564	0.0118	0.0079
AR	232	0.0076	0.0727	0.0229	0.0119
ZA	232	0.0013	0.0799	0.0123	0.0093

This table reports the performance of the daily volatility of the 19 stock markets of sample countries (US: the United States, CN: China, JP: Japan, DE: Germany, IN: India, GB: United Kingdom, FR: France, IT: Italy, BR: Brazil, CA: Canada, KR: South Korea, RU: Russia, AU: Australia, MX: Mexico, ID: Indonesia, SA: Saudi Arabia, TR: Turkey, AR: Argentina, ZA: South Africa) during COVID-19, based on the method proposed by Alizadeh et al. (2002). The sample interval is from 31 December 2019 to 30 November 2020, which comprises 232 trading days.

Table A3  
Total connectedness of 19 countries during COVID-19

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	18.82	1.42	5.31	8.67	2.24	8.41	6.50	8.11	5.06	12.33	0.87	2.52	5.72	2.16	2.08	2.59	2.22	1.29	3.69	81.18
CN	0.71	55.45	3.73	1.50	2.76	3.11	0.70	5.39	1.24	6.23	0.87	0.20	3.68	2.45	2.19	1.41	5.60	1.51	1.27	44.55
JP	3.14	0.91	19.18	5.97	1.83	10.98	3.88	9.84	5.94	2.83	1.31	4.45	6.77	3.22	0.87	4.68	2.70	6.17	5.35	80.82
DE	5.48	0.55	5.22	15.00	2.78	10.76	11.84	11.66	5.73	5.59	0.57	2.94	5.16	2.21	1.09	3.47	2.36	4.40	3.18	85.00
IN	3.35	0.66	3.74	4.35	19.54	9.72	2.61	8.96	7.84	4.85	2.74	4.64	5.74	3.85	1.08	7.18	2.04	4.56	2.54	80.46
GB	6.17	0.70	4.44	11.03	2.91	17.91	8.78	11.23	5.63	7.08	0.31	2.36	3.30	1.98	1.71	3.20	2.96	4.24	4.05	82.09
FR	5.63	0.48	5.63	13.35	2.62	11.12	13.47	11.38	6.88	6.19	0.39	2.52	4.99	2.23	1.09	2.86	2.14	3.83	3.20	86.53
IT	4.23	0.36	5.06	10.43	4.04	12.34	8.18	15.48	8.36	4.74	0.42	3.91	4.36	2.26	0.84	4.68	2.12	4.76	3.41	84.52
BR	3.69	0.88	6.55	3.69	3.98	8.16	2.74	8.54	21.51	3.69	1.02	7.17	6.45	3.10	0.99	7.82	3.90	2.92	3.21	78.49
CA	9.38	1.17	6.10	7.01	6.40	8.25	4.74	10.08	7.18	15.79	1.19	2.71	6.59	0.92	0.71	5.72	2.27	2.00	1.78	84.21
KR	1.11	0.91	5.46	3.45	7.43	7.84	2.41	7.66	8.85	1.78	28.56	2.64	2.74	0.61	3.46	3.75	2.79	6.06	2.50	71.44
RU	4.39	1.58	5.02	5.30	2.86	10.00	4.02	7.74	8.12	4.28	0.39	21.91	3.82	1.92	0.47	5.49	3.46	3.52	5.71	78.09
AU	3.88	1.96	6.24	7.19	5.36	9.96	4.84	9.97	5.99	4.49	1.41	3.97	16.00	3.47	2.41	4.57	1.76	4.27	2.25	84.00
MX	3.63	2.02	4.07	5.24	2.98	6.81	4.34	7.12	7.71	3.04	0.79	5.74	3.80	26.84	0.46	4.51	2.47	4.08	4.35	73.16
ID	3.84	2.30	4.11	3.44	2.58	5.47	2.22	3.05	5.31	4.16	3.07	2.40	3.50	5.66	35.66	2.02	2.43	1.93	6.84	64.34
SA	5.42	1.70	4.61	3.19	2.16	5.36	2.95	3.46	3.94	2.42	0.30	6.48	2.82	0.78	1.52	41.78	1.92	3.91	5.27	58.22
TR	1.98	0.87	2.54	6.06	1.77	7.63	3.82	5.90	2.69	1.76	2.99	3.32	2.27	0.40	1.54	2.31	40.39	9.21	2.54	59.61
AR	0.41	0.53	3.90	5.46	2.95	4.30	4.82	6.46	5.82	1.35	2.99	0.95	2.42	4.48	1.44	3.22	2.74	42.58	3.19	57.42
ZA	5.44	1.84	3.39	5.88	0.47	6.73	6.06	4.99	3.90	5.16	0.71	6.12	3.70	5.15	2.89	3.75	3.61	3.32	26.89	73.11
TO	71.86	20.84	85.12	111.20	58.13	146.95	85.44	141.55	106.19	81.98	22.34	65.06	77.85	46.86	26.83	73.23	49.51	71.99	64.34	
NET	-9.31	-23.71	4.29	26.19	-22.33	64.86	-1.09	57.02	27.70	-2.23	-49.10	-13.03	-6.16	-26.29	-37.52	15.02	-10.10	14.56	-8.77	74.07

This table reports the connectedness performance of the 19 sample countries during COVID-19, based on the method proposed by Diebold and Yilmaz (2012). Except for diagonal elements, the elements of the 19\*19 matrix in the upper-left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number '1.42' in the first row represents the connectedness from China to the United States. The 'TO' row displays the total sending connectedness of each market, the 'FROM' column displays the total receiving connectedness of each market and the 'NET' row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market, by calculating the average of sending connectedness or receiving connectedness. In addition, all the data except the underlined data are significantly larger than 0 at the 10 percent level, based on  $t$ -test.

Table A4  
High-frequency connectedness of 19 countries during COVID-19

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	5.47	0.21	0.32	0.95	0.35	0.30	1.06	0.52	0.24	2.53	0.08	0.32	0.48	0.57	0.69	0.54	0.32	0.19	0.53	10.23
CN	0.52	14.19	1.40	0.49	0.25	1.62	0.19	1.06	0.63	0.25	0.72	0.10	0.70	0.48	1.89	0.98	2.82	1.02	1.15	16.26
JP	0.87	0.40	6.74	0.16	0.25	0.93	0.37	0.52	1.19	0.52	0.76	1.26	0.91	1.82	0.51	1.22	0.12	1.40	2.85	16.06
DE	0.82	0.29	1.20	5.06	0.50	1.48	4.62	2.49	0.24	0.74	0.42	0.74	1.02	0.80	0.51	1.27	0.33	0.72	1.19	19.38
IN	0.49	0.51	1.14	1.18	11.05	3.75	0.62	2.82	2.37	1.02	1.91	3.00	3.02	2.51	1.01	4.05	1.51	1.30	1.74	33.95
GB	0.65	0.51	0.62	1.93	0.84	4.76	2.56	1.75	0.50	1.28	0.14	0.38	0.58	0.71	0.63	1.02	0.09	0.33	1.56	16.08
FR	0.45	0.14	1.18	3.24	0.32	1.25	5.08	1.64	0.44	0.82	0.18	0.59	0.69	0.64	0.36	1.31	0.36	0.76	1.02	15.38
IT	0.43	0.19	0.96	2.28	0.99	0.98	2.39	3.69	0.23	0.67	0.27	1.12	1.08	0.97	0.28	1.72	0.20	0.44	0.97	16.17
BR	0.59	0.31	2.15	0.43	1.37	2.13	0.32	1.67	8.25	0.62	0.84	1.10	2.23	2.63	0.61	2.37	1.34	0.48	1.92	23.14
CA	2.24	0.10	0.75	0.32	0.76	0.10	0.52	0.69	0.88	4.46	0.43	0.74	0.39	0.34	0.27	2.17	0.19	0.58	0.66	12.13
KR	0.30	0.67	1.44	1.38	2.36	1.68	0.76	1.61	1.70	0.50	12.08	0.94	1.50	0.60	0.47	1.80	2.25	4.11	1.79	25.85
RU	0.25	1.01	1.16	0.47	1.15	0.99	0.49	0.24	0.95	0.10	0.30	8.29	0.72	0.94	0.21	1.06	0.75	0.67	1.71	13.18
AU	1.16	1.57	1.35	0.85	1.75	1.01	1.06	1.75	1.59	<u>1.27</u>	0.83	1.48	9.63	2.69	1.50	1.67	0.55	1.38	1.00	24.46
MX	1.46	2.00	1.88	2.04	2.49	1.53	2.01	3.24	3.76	0.88	0.78	3.84	3.18	22.00	0.39	3.60	1.82	1.45	3.22	39.38
ID	0.86	2.16	1.86	0.61	1.73	2.31	1.12	0.52	3.31	0.81	1.30	1.14	2.00	2.61	24.86	1.70	1.66	0.39	4.40	30.49
SA	2.30	0.45	0.33	0.38	1.07	0.84	1.13	0.74	0.88	2.21	0.13	0.92	1.22	0.77	1.44	17.39	0.50	0.46	3.37	19.14
TR	1.98	0.87	0.47	1.52	1.06	1.17	1.41	1.40	1.17	1.05	0.64	1.52	1.87	0.40	1.14	1.24	17.82	2.25	2.21	23.35
AR	0.38	0.51	2.01	3.01	1.01	3.22	3.10	1.44	1.09	0.53	2.92	0.84	0.74	4.11	0.27	0.45	1.68	26.96	2.15	29.44
ZA	1.53	1.28	0.21	1.78	0.26	1.97	2.90	1.11	1.74	0.76	0.34	3.90	0.68	3.80	1.76	2.17	1.22	0.38	19.62	27.80
TO	17.29	13.19	20.42	23.03	<u>18.53</u>	27.27	26.64	25.22	22.92	16.55	12.99	23.94	23.02	27.37	13.93	30.34	17.72	18.30	33.42	
NET	7.06	-3.07	4.36	3.64	-15.42	11.19	11.26	9.05	<u>-0.22</u>	4.42	-12.87	10.76	<u>-1.44</u>	-12.21	-16.57	11.20	<u>-5.63</u>	-11.15	<u>5.63</u>	21.69

This table reports the high-frequency (0–5 days) connectedness performance of the 19 sample countries during COVID-19, based on the method proposed by Barunik and Křehlík (2018). Except for diagonal elements, the elements of the 19\*19 matrix in the upper left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number ‘0.21’ in the first row represents the connectedness from China to the United States. The ‘TO’ row displays the total sending connectedness of each market, the ‘FROM’ column displays the total receiving connectedness of each market and the ‘NET’ row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market on this sub-band. All the data except the underlined data are significantly larger than 0 at the 10 percent level, based on *t*-test.

Table A5  
Low-frequency connectedness of 19 countries during COVID-19

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	13.36	1.21	4.99	7.72	1.88	8.11	5.43	7.58	4.82	9.80	0.78	2.20	5.23	1.59	1.39	2.04	1.89	1.10	3.16	70.95
CN	0.19	41.26	2.33	1.01	2.51	1.50	0.51	4.33	0.60	5.98	0.15	0.10	2.98	1.97	0.30	0.43	2.78	0.49	0.12	28.29
JP	2.27	0.50	12.44	5.81	1.58	10.04	3.51	9.32	4.75	2.30	0.55	3.19	5.87	1.40	0.35	3.46	2.58	4.77	2.50	64.77
DE	4.66	0.26	4.02	9.94	2.28	9.29	7.22	9.18	5.49	4.85	0.14	2.20	4.14	1.41	0.58	2.20	2.03	3.68	1.99	65.62
IN	2.86	0.16	2.61	3.17	8.49	5.97	1.99	6.14	5.47	3.84	0.83	1.64	2.72	1.34	0.07	3.13	0.53	3.26	0.80	46.51
GB	5.52	0.18	3.82	9.10	2.07	13.15	6.22	9.48	5.13	5.80	0.18	1.99	2.72	1.27	1.09	2.18	2.87	3.91	2.48	66.01
FR	5.18	0.33	4.45	10.10	2.30	9.87	8.39	9.74	6.44	5.37	0.21	1.94	4.30	1.60	0.73	1.55	1.78	3.07	2.18	71.15
IT	3.80	0.17	4.11	8.15	3.06	11.36	5.79	11.78	8.13	4.07	0.15	2.79	3.28	1.30	0.56	2.96	1.92	4.32	2.45	68.35
BR	3.10	0.56	4.40	3.26	2.61	6.02	2.42	6.86	13.26	3.07	0.18	6.07	4.22	0.47	0.38	5.45	2.56	2.43	1.29	55.36
CA	7.13	1.07	5.35	6.69	5.63	8.14	4.22	9.40	6.30	11.33	0.76	1.97	6.20	0.58	0.45	3.56	2.08	1.41	1.12	72.08
KR	0.81	0.24	4.02	2.07	5.07	6.16	1.65	6.05	7.15	1.28	16.48	1.70	1.24	0.01	0.99	1.96	0.54	1.94	0.71	45.59
RU	4.14	0.58	3.86	4.83	1.70	9.01	3.53	7.50	7.16	4.18	0.08	13.61	3.10	0.99	0.26	4.42	2.71	2.85	4.00	64.91
AU	2.71	0.39	4.89	6.34	3.61	8.95	3.78	8.22	4.40	3.21	0.58	2.49	6.37	0.78	0.91	2.91	1.21	2.89	1.25	59.54
MX	2.17	0.02	2.19	3.21	0.49	5.28	2.33	3.88	3.95	2.15	0.01	1.90	0.62	4.84	0.07	0.91	0.65	2.63	1.14	33.58
ID	2.98	0.14	2.25	2.83	0.86	3.16	1.10	2.53	2.00	3.35	1.76	1.26	1.50	3.05	10.79	0.32	0.77	1.55	2.45	33.85
SA	3.11	1.25	4.28	2.80	1.08	4.52	1.82	2.72	3.07	0.21	0.17	5.57	1.60	0.01	0.08	24.39	1.42	3.45	1.91	39.08
TR	0.00	0.00	2.07	4.53	0.71	6.46	2.41	4.50	1.52	0.72	2.36	1.79	0.41	0.00	0.40	1.07	22.58	6.96	0.33	36.25
AR	0.03	0.02	1.89	2.45	1.95	1.08	1.72	5.02	4.72	0.82	0.07	0.11	1.67	0.38	1.17	2.77	1.06	15.62	1.04	27.98
ZA	3.91	0.56	3.17	4.10	0.21	4.76	3.16	3.88	2.16	4.40	0.37	2.12	3.02	1.35	1.13	1.58	2.39	2.94	7.27	45.32
TO	54.57	7.65	64.70	88.17	39.60	119.68	58.81	116.32	83.27	65.42	9.35	41.12	54.82	19.50	12.90	42.90	31.78	53.69	30.92	
NET	-16.38	-20.64	-0.07	22.55	-6.91	53.67	-12.34	47.97	27.91	-6.65	-36.24	-23.79	-4.72	-14.08	-20.95	3.82	-4.47	25.71	-14.40	52.38

This table reports the low-frequency (more than 5 days) connectedness performance of the 19 sample countries during COVID-19, based on the method proposed by Barunik and Křehlík (2018). Except for diagonal elements, the elements of the 19\*19 matrix in the upper left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number '1.21' in the first row represents the connectedness from China to the United States. The 'TO' row displays the total sending connectedness of each market, the 'FROM' column displays the total receiving connectedness of each market and the 'NET' row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market on this sub-band. All the data except the underlined data are significantly larger than 0 at the 10 percent level, based on *t*-test.

Table A6  
Total connectedness of 19 countries during the subprime mortgage crisis

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	20.30	0.51	3.00	6.79	2.19	6.08	5.49	7.27	9.63	11.91	0.77	2.12	1.47	9.25	1.00	1.26	0.82	7.34	2.80	79.70
CN	2.94	53.40	1.25	1.59	2.43	2.31	0.87	2.80	3.76	1.94	1.48	2.70	0.95	3.54	6.19	2.53	4.92	1.73	2.66	46.60
JP	9.36	0.19	26.55	4.85	2.98	4.06	4.70	3.72	3.82	6.83	4.94	2.65	2.61	5.87	2.61	1.36	1.26	9.44	2.18	73.45
DE	7.73	0.17	2.89	19.27	2.33	12.19	12.87	8.31	2.83	6.35	0.89	2.53	1.61	5.79	0.77	2.92	2.62	3.97	3.99	80.73
IN	4.63	0.47	3.18	4.89	37.27	4.69	4.59	2.00	3.57	4.93	2.34	1.70	1.35	5.87	4.03	1.09	3.24	6.59	3.58	62.73
GB	7.40	0.31	2.14	11.56	2.68	17.76	10.84	8.18	4.76	6.42	0.94	3.67	1.54	6.10	1.23	2.41	2.74	3.60	5.72	82.24
FR	7.90	0.19	3.01	12.99	2.07	12.06	17.54	9.69	4.20	7.10	0.52	2.56	1.43	5.82	1.09	3.15	1.90	3.42	3.36	82.46
IT	8.72	0.32	2.04	9.02	1.16	9.38	9.63	20.20	5.07	8.33	0.66	3.62	0.87	6.07	1.36	2.88	1.97	4.53	4.18	79.80
BR	9.82	0.17	1.91	2.27	1.30	2.85	2.97	5.98	28.29	11.32	0.56	1.87	1.40	10.47	2.48	1.63	1.43	10.27	3.01	71.71
CA	12.11	0.08	2.49	4.31	1.20	4.60	4.80	8.58	9.92	24.05	0.39	2.09	1.77	7.98	1.27	2.86	0.78	8.55	2.18	75.95
KR	8.00	1.07	5.79	2.66	6.09	1.20	0.76	0.97	2.72	4.53	41.94	1.26	1.85	5.74	0.89	1.26	0.99	10.88	1.41	58.06
RU	4.53	0.41	1.30	4.45	2.61	6.79	4.34	6.42	7.59	7.50	0.91	26.70	2.36	6.18	3.65	3.93	1.43	3.04	5.88	73.30
AU	7.01	0.77	3.31	3.37	2.71	5.10	3.07	2.74	5.83	5.74	1.25	2.91	31.16	7.14	3.96	1.90	2.26	3.42	6.38	68.84
MX	11.76	0.35	2.46	5.50	2.13	5.92	4.20	5.58	10.16	9.41	1.60	1.87	1.09	21.62	1.76	0.54	2.18	8.53	3.34	78.38
ID	3.29	0.89	1.63	0.63	4.14	2.04	0.91	3.64	6.95	7.82	1.36	4.09	2.00	6.35	42.90	0.88	2.86	5.23	2.40	57.10
SA	6.10	0.81	1.06	3.80	1.95	5.25	4.86	6.02	7.55	8.12	0.30	6.15	0.14	4.60	0.88	35.72	1.31	3.16	2.21	64.28
TR	3.04	0.07	1.46	5.42	3.18	6.46	4.59	3.86	5.33	2.57	0.88	2.34	2.22	7.92	6.45	1.15	37.22	2.39	3.45	62.78
AR	8.13	0.41	2.34	2.42	0.91	2.09	2.61	5.12	13.32	11.74	3.56	2.44	0.93	8.42	2.25	2.56	1.28	27.08	2.40	72.92
ZA	5.04	0.25	1.11	5.99	3.89	8.70	4.20	5.52	4.35	6.32	2.02	4.77	2.56	7.47	3.06	1.13	3.45	3.87	26.30	73.70
TO	127.49	7.42	42.39	92.51	45.94	101.78	86.30	96.40	111.34	128.87	25.37	51.34	28.15	120.56	44.92	35.45	37.44	99.95	61.12	
NET	47.79	-39.18	-31.06	11.78	-16.79	19.54	3.84	16.59	39.64	52.92	-32.69	-21.96	-40.69	42.17	-12.18	-28.83	-25.34	27.03	-12.58	70.78

This table reports the connectedness performance of the 19 sample countries during the subprime mortgage crisis, based on the method proposed by Diebold and Yilmaz (2012). Except for diagonal elements, the elements of the 19\*19 matrix in the upper left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number '0.51' in the first row represents the connectedness from China to the United States. The 'TO' row displays the total sending connectedness of each market, the 'FROM' column displays the total receiving connectedness of each market and the 'NET' row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market, by calculating the average of sending connectedness or receiving connectedness. In addition, all the data except the underlined data are significantly larger than 0 at the 10 percent level, based on *t*-test.

Table A7  
High-frequency connectedness of 19 countries during the subprime mortgage crisis

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	6.63	0.50	0.38	1.61	0.38	0.77	1.04	0.94	1.49	1.47	0.27	0.12	0.14	2.31	0.21	0.27	0.24	0.88	0.40	13.42
CN	0.55	27.56	0.20	0.65	0.18	1.66	0.63	0.96	1.10	0.74	0.67	1.88	0.38	1.44	0.46	1.02	1.40	0.83	1.53	16.28
JP	1.43	0.19	15.98	0.52	0.79	0.43	0.89	0.27	0.21	0.96	1.40	0.69	1.28	0.14	0.22	0.77	0.58	0.39	0.18	11.33
DE	0.88	0.13	0.38	7.56	0.47	4.08	4.66	2.01	0.11	0.42	0.20	0.37	0.29	0.67	0.06	0.72	0.71	0.39	0.93	17.49
IN	1.04	0.46	1.58	2.24	20.42	2.69	2.46	0.73	0.10	0.26	0.65	1.36	0.56	0.33	0.67	0.98	0.40	2.15	2.43	21.10
GB	1.19	0.29	0.87	5.43	0.85	9.28	5.42	2.72	0.48	0.73	0.14	1.24	0.84	1.23	0.04	0.42	1.07	0.41	1.80	25.15
FR	0.67	0.16	0.78	5.03	0.43	4.45	8.25	2.59	0.03	0.44	0.16	0.22	0.32	0.70	0.12	0.62	0.76	0.49	0.50	18.38
IT	0.92	0.30	0.68	2.81	0.21	2.66	3.11	6.83	0.62	0.87	0.14	0.64	0.32	0.50	0.41	0.52	0.71	0.39	0.99	16.80
BR	3.11	0.17	0.65	0.73	0.57	0.47	0.50	1.14	11.28	2.32	0.19	0.61	0.61	3.86	0.70	0.11	0.90	2.68	0.38	19.70
CA	2.66	0.08	0.47	1.31	0.46	0.68	1.03	1.63	2.30	9.69	0.13	0.88	0.63	2.36	0.60	0.76	0.61	2.09	0.58	19.29
KR	0.96	0.79	3.31	0.26	0.78	0.60	0.42	0.47	1.13	0.25	13.00	0.60	1.32	0.67	0.07	1.26	0.17	1.52	0.35	14.92
RU	0.91	0.37	0.28	1.30	0.66	2.62	1.27	1.19	1.11	0.37	0.11	10.78	0.69	1.05	1.19	1.38	0.77	0.22	1.01	16.52
AU	1.86	0.75	1.91	0.61	0.15	1.20	0.85	0.57	1.36	1.02	0.55	0.96	18.75	1.80	1.12	1.17	0.64	0.49	0.24	17.26
MX	2.37	0.35	0.69	1.36	0.79	1.13	0.80	0.88	1.95	1.66	0.14	0.51	0.43	8.76	0.29	0.16	0.58	0.67	0.40	15.17
ID	0.74	0.66	0.26	0.28	0.69	0.62	0.24	0.73	0.30	0.31	0.29	0.79	0.56	0.27	14.54	0.67	1.44	0.40	0.72	9.98
SA	0.29	0.09	0.02	0.55	0.69	0.90	0.45	0.43	0.56	0.77	0.20	0.56	0.14	0.30	0.40	10.62	1.29	1.35	0.78	9.78
TR	0.64	0.05	0.72	2.79	0.32	3.00	2.02	1.78	0.43	0.44	0.45	0.49	0.64	1.32	0.32	0.78	21.78	0.95	1.62	18.79
AR	1.31	0.40	1.64	0.40	0.41	0.34	0.62	0.76	3.41	2.26	1.33	0.32	0.25	1.55	0.64	1.23	0.53	14.51	0.30	17.69
ZA	0.28	0.14	0.56	2.21	1.66	2.92	1.52	1.53	0.70	1.00	0.05	1.02	0.73	0.80	0.41	0.27	1.16	0.61	14.37	17.57
TO	21.82	5.88	15.38	30.10	10.49	31.23	27.92	21.33	17.40	16.30	7.09	13.25	10.05	21.31	7.93	13.11	13.97	16.92	15.13	15.13
NET	8.39	-10.40	4.06	12.61	-10.61	6.08	9.54	4.53	-2.30	-2.99	-7.83	-3.26	-7.22	6.14	-2.05	3.33	-4.82	-0.77	-2.44	16.66

This table reports the high-frequency (0–5 days) connectedness performance of the 19 sample countries during the subprime mortgage crisis, based on the method proposed by Barunik and Křehlik (2018). Except for diagonal elements, the elements of the 19\*19 matrix in the upper left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number '0.50' in the first row represents the connectedness from China to the United States. The 'TO' row displays the total sending connectedness of each market, the 'FROM' column displays the total receiving connectedness of each market and the 'NET' row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market on this sub-band. All the data except the underlined data are significantly larger than 0 at the 10 percent level, based on *t*-test.

Table A8  
Low-frequency connectedness of 19 countries during the subprime mortgage crisis

	US	CN	JP	DE	IN	GB	FR	IT	BR	CA	KR	RU	AU	MX	ID	SA	TR	AR	ZA	FROM
US	13.66	0.01	2.62	5.18	1.81	5.31	4.45	6.32	8.14	10.44	0.50	2.00	1.32	6.94	0.79	0.99	0.59	6.46	2.41	66.28
CN	2.38	25.84	1.05	0.94	2.25	0.65	0.24	1.84	2.67	1.20	0.81	0.82	0.57	2.10	5.73	1.51	3.52	0.91	1.13	30.32
JP	7.93	0.00	10.57	4.34	2.19	3.64	3.81	3.45	3.60	5.87	3.54	1.97	1.33	5.73	2.39	0.59	0.68	9.05	2.00	62.12
DE	6.85	0.03	2.51	11.71	1.86	8.10	8.21	6.30	2.72	5.92	0.69	2.16	1.32	5.12	0.71	2.20	1.91	3.58	3.06	63.24
IN	3.59	0.01	1.60	2.64	16.85	2.01	2.13	1.27	3.46	4.67	1.69	0.33	0.79	5.54	3.36	0.11	2.83	4.44	1.15	41.64
GB	6.21	0.02	1.28	6.14	1.84	8.48	5.42	5.46	4.27	5.69	0.80	2.44	0.70	4.87	1.20	2.00	1.67	3.19	3.92	57.09
FR	7.23	0.03	2.23	7.96	1.64	7.61	9.28	7.11	4.18	6.66	0.36	2.35	1.20	5.12	0.97	2.53	1.14	2.93	2.86	64.08
IT	7.79	0.01	1.37	6.21	0.95	6.73	6.52	13.37	4.45	7.47	0.51	2.98	0.54	5.56	0.95	2.36	1.26	4.14	3.19	63.00
BR	6.71	0.00	1.26	1.53	0.74	2.38	2.47	4.84	17.01	8.99	0.37	1.27	0.79	6.60	1.77	1.52	0.53	7.59	2.63	52.01
CA	9.44	0.00	2.01	3.00	0.74	3.92	3.77	6.95	7.61	14.35	0.26	1.20	1.14	5.62	0.67	2.10	0.17	6.46	1.59	56.66
KR	7.04	0.29	2.49	2.40	5.31	0.60	0.34	0.50	1.59	4.28	28.94	0.65	0.53	5.06	0.82	0.00	0.82	9.36	1.06	43.14
RU	3.61	0.04	1.02	3.15	1.95	4.16	3.07	5.24	6.47	7.13	0.79	15.91	1.67	5.13	2.45	2.55	0.66	2.82	4.87	56.79
AU	5.14	0.02	1.40	2.76	2.56	3.90	2.21	2.16	4.47	4.72	0.70	1.95	12.40	5.34	2.83	0.72	1.62	2.93	6.14	51.58
MX	9.39	0.00	1.78	4.14	1.34	4.79	3.41	4.70	8.21	7.75	1.45	1.36	0.66	12.86	1.47	0.38	1.60	7.85	2.94	63.21
ID	2.56	0.23	1.37	0.35	3.45	1.42	0.67	2.90	6.65	7.51	1.06	3.30	1.44	6.07	28.36	0.21	1.42	4.83	1.68	47.12
SA	5.81	0.72	1.05	3.25	1.26	4.35	4.41	5.60	6.98	7.35	0.10	5.59	0.00	4.30	0.49	25.10	0.01	1.81	1.43	54.50
TR	2.39	0.01	0.74	2.62	2.85	3.46	2.57	2.09	4.90	2.13	0.43	1.84	1.58	6.60	6.13	0.37	15.44	1.44	1.82	43.99
AR	6.83	0.01	0.70	2.02	0.50	1.74	1.99	4.36	9.91	9.48	2.23	2.12	0.68	6.87	1.61	1.33	0.75	12.57	2.10	55.23
ZA	4.75	0.11	0.54	3.78	2.23	5.78	2.68	3.99	3.65	5.33	1.97	3.75	1.83	6.67	2.65	0.86	2.30	3.25	11.92	56.13
TO	105.67	1.54	27.01	62.42	35.45	70.55	58.38	75.06	93.94	112.57	18.28	38.09	18.11	99.24	36.99	22.34	23.47	83.03	45.99	
NET	39.39	-28.78	-35.11	-0.83	-6.19	13.46	-5.70	12.06	41.93	55.91	-24.86	-18.70	-33.47	36.04	-10.13	-32.16	-20.52	27.80	-10.14	54.11

This table reports the low-frequency (more than 5 days) connectedness performance of the 19 sample countries during the subprime mortgage crisis, based on the method proposed by Barunik and Křehlík (2018). Except for diagonal elements, the elements of the 19\*19 matrix in the upper left corner represent shock intensity from the market represented by this column to the market represented by this row. For example, the number '0.01' in the first row represents the connectedness from China to the United States. The 'TO' row displays the total sending connectedness of each market, the 'FROM' column displays the total receiving connectedness of each market and the 'NET' row displays the total net connectedness of each market. The element in the bottom right corner represents the total connectedness state of the whole global stock market on this sub-band. All the data except the underlined data are significantly larger than 0 at the 10 percent level, based on *t*-test.

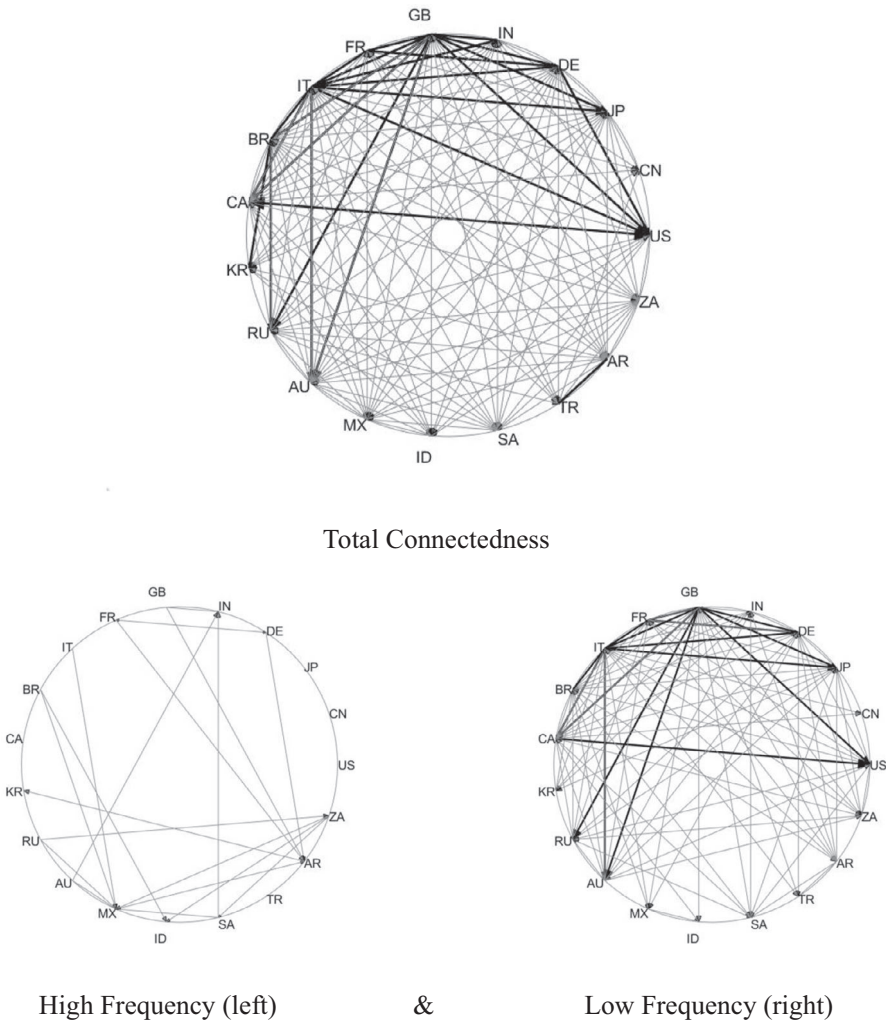


Figure A1 The connectedness network during COVID-19. This figure shows the total connectedness network among the 19 sample countries during the COVID-19 pandemic based on the method proposed by Diebold and Yilmaz (2012) and the sub-band connectedness network based on the method proposed by Baruník and Křehlík (2018). The sample interval is from 31 December 2019 to 30 November 2020. The line width indicates the strength of connectedness, and the arrow indicates the direction of connectedness. For example, in 'Total Connectedness', the black line between the United States (US) and Canada (CA) is wider than the grey lines, which indicates that the pairwise connectedness is larger than other forms of connectedness. Meanwhile, the arrow points to Canada, which means that the line represents the intensity of the shock from the United States to Canada. In addition, to show better visual output, we remove connectedness whose size is under 3 percent and choose 8 percent as the threshold to divide the remaining connectedness into two levels. If the size is larger than 8 percent, the connectedness is represented by a black line.

Otherwise, the connectedness is represented by a grey line.

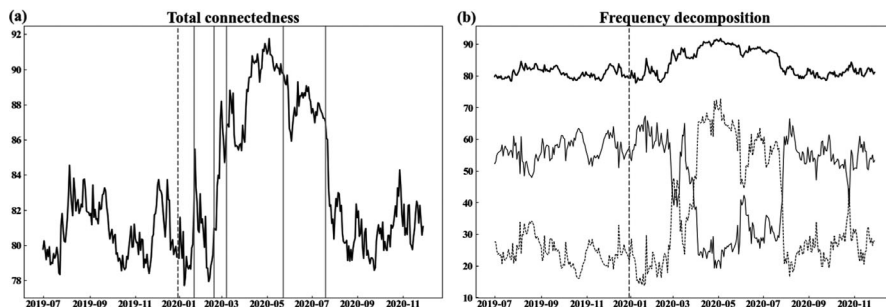


Figure A2 Dynamic connectedness of 19 countries. Plot (a) shows the total connectedness dynamics of 19 countries during the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents the connectedness value. The thick black line indicates the total connectedness based on the definition of Diebold and Yilmaz (2012).

The vertical lines represent several important time points during the COVID-19 pandemic. The events from left to right are as follows: (1) date of the Wuhan Municipal Health Commission's first notification of an unknown pneumonia epidemic (31 December 2019); (2) date on which Wuhan announced the closure of cities due to COVID-19 (23 January 2020); (3) timing of the rapid spread and gradual outbreak of COVID-19 around the world (late February 2020); (4) the first trading day after the negotiations between OPEC and Russia broke down (9 March 2020); (5) date on which *The Lancet* published the results of the world's first human trial of a COVID-19 vaccine, showing that the vaccine is safe, well tolerated, and can induce an immune response against COVID-19 in the human body (22 May 2020); (6) date on which *The Lancet* released the latest results of two COVID-19 vaccine I/II clinical trials, both of which can generate an immune response to the coronavirus (SARS-CoV-2) and can induce a highly effective T-cell immune response (20 July 2020); and the date on which the European Union reached a deal for a €750 billion recovery fund (21 July 2020).

Plot (b) shows the sub-band connectedness dynamics of 19 countries during the sample interval from 1 January 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents the connectedness value. The thick black line indicates total connectedness based on the definition of Diebold and Yilmaz (2012). The thin black line (high-frequency) and the black dotted line (low-frequency) represent frequency connectedness based on the definitions of Baruník and Křehlík (2018). The vertical grey dotted line represents the starting date for the sample studied in the article.

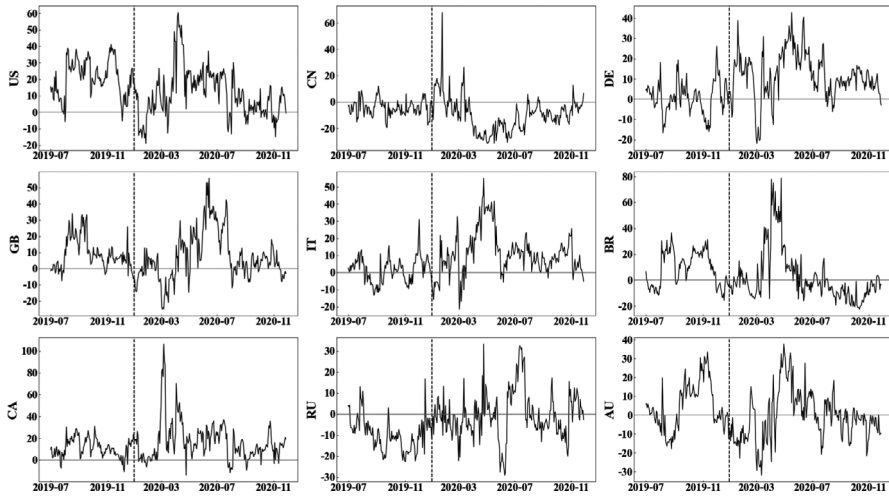


Figure A3 Dynamic *NET* connectedness of each market. This figure shows the *NET* connectedness dynamics of each country with the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents connectedness value. The thick black line indicates the *NET* connectedness defined by Diebold and Yilmaz (2012). The vertical grey dotted line represents the starting date of the sample studied in the article. To simplify the image, we only included dynamic *NET* connectedness for nine typical countries (US: the United States, CN: China, DE: Germany, GB: United Kingdom, IT: Italy, BR: Brazil, CA: Canada, RU: Russia, AU: Australia) in Appendix I; the figures of dynamic connectedness of all countries are included in Appendix II.

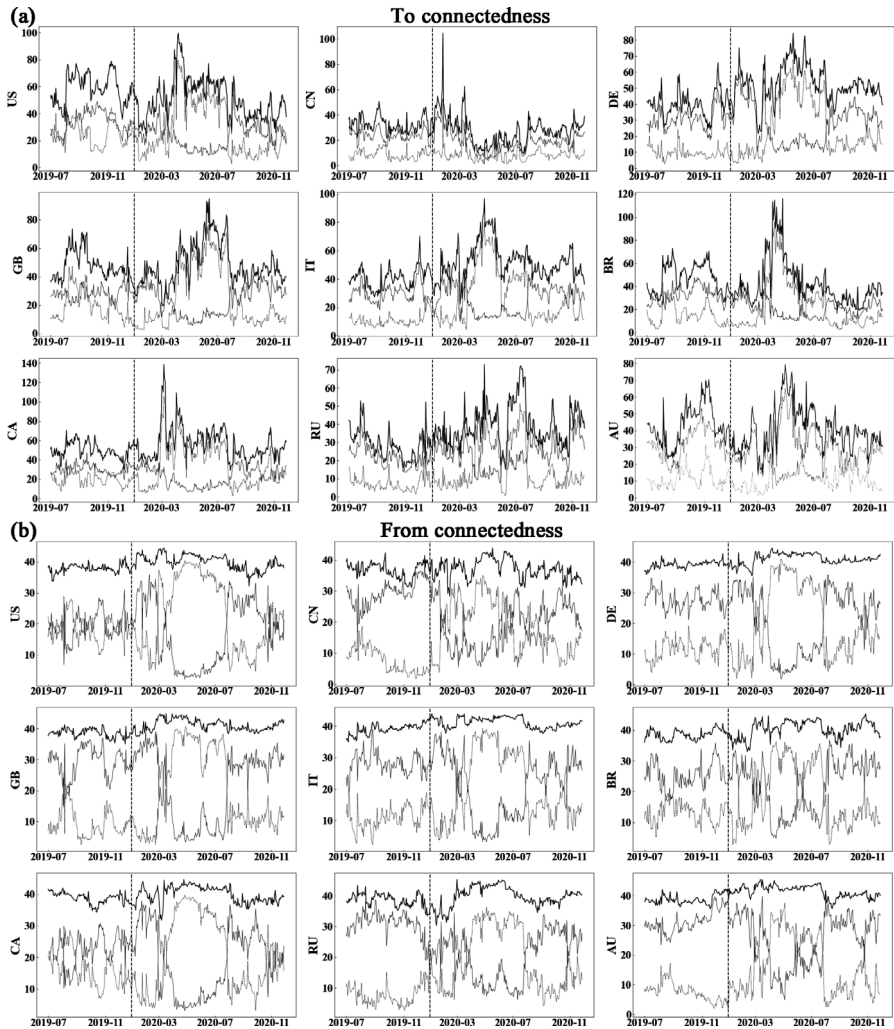
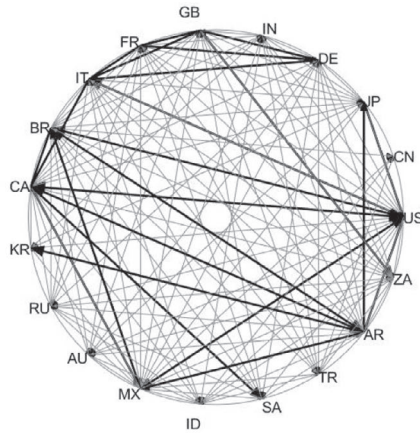
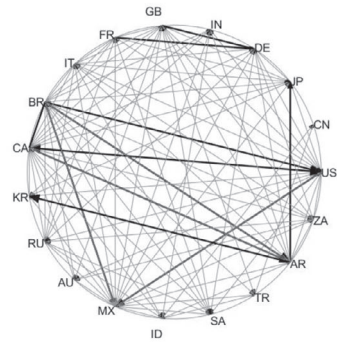
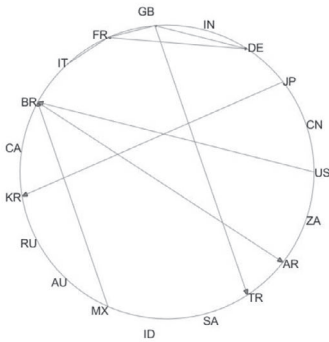


Figure A4 Dynamic *TO* & *FROM* connectedness of each market on frequency bands. This figure shows the *TO* connectedness (Plot(a)) and *FROM* connectedness (Plot(b)) dynamics of each country with the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents connectedness value. The thick black line indicates the total *TO* (*FROM*) connectedness defined by Diebold and Yilmaz (2012). The thin black line (high-frequency) and the black dotted line (low-frequency) represent the frequency *TO* (*FROM*) connectedness defined by Baruník and Křehlík (2018). The vertical grey dotted line represents the starting date of the sample studied in the article.



Total Connectedness



High Frequency Connectedness(left) & Low Frequency Connectedness(right)

Figure A5 Connectedness network during the subprime mortgage crisis. This figure shows the total connectedness network between the 19 sample countries during the subprime mortgage crisis based on the method proposed by Diebold and Yilmaz (2012) and the sub-band connectedness network based on the method proposed by Barunik and Křehlík (2018). The sample interval is from 1 August 2007 to 31 March 2009. The line width indicates the size of connectedness and the arrow indicates the direction of connectedness. For example, in ‘Total Connectedness’, the black line between United States (US) and Canada (CA) is wider than the grey lines, which indicates the pairwise connectedness is larger. Meanwhile, the arrow points to Canada, which means the line represents the shock intensity from United States to Canada. In addition, to show better visual output, we remove connectedness whose size is under 3 percent and choose 8 percent as the threshold to divide the remaining connectedness into two levels. If the size is larger than 8 percent, the connectedness is represented by a black line. Otherwise, the connectedness is represented by a grey line.

## Appendix II

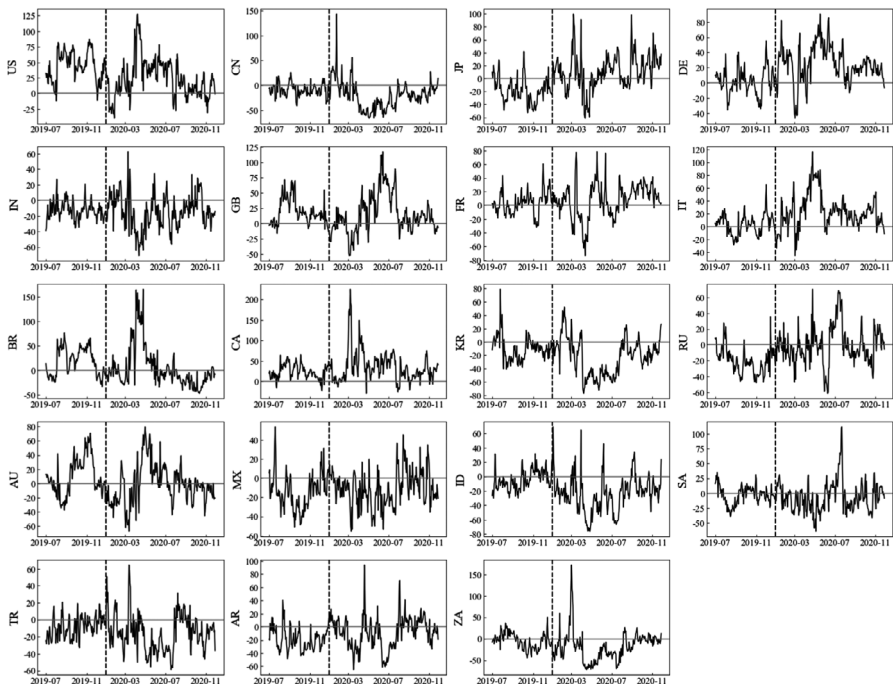


Figure A6 Dynamic *NET* connectedness of each market (19 countries). This figure shows the *NET* connectedness dynamics of each market (19 countries) with the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents connectedness value. The thick black line indicates the *NET* connectedness defined by Diebold and Yilmaz (2012). The vertical grey dotted line represents the starting date of the sample studied in the article.

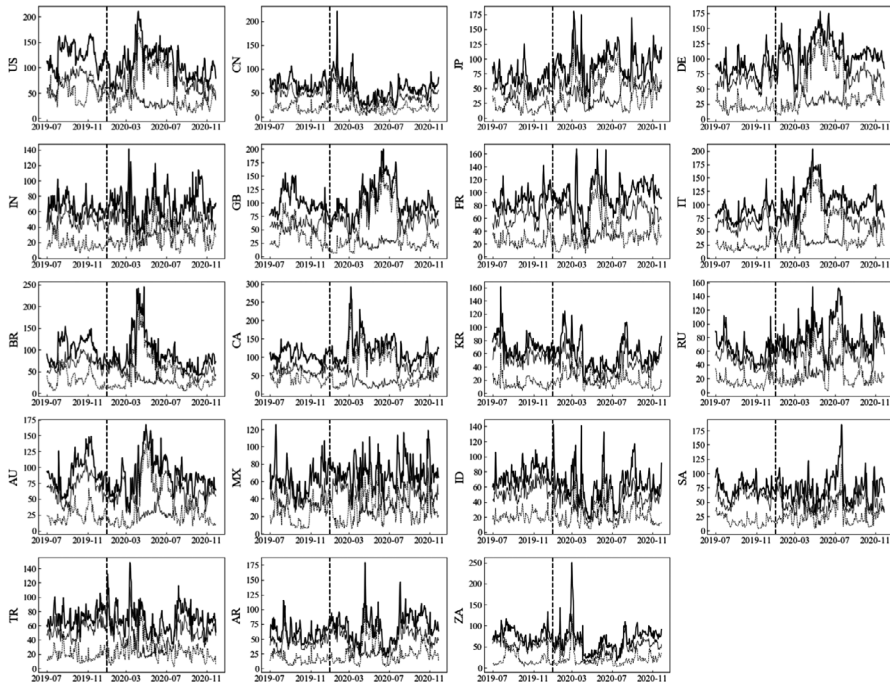


Figure A7 Dynamic *TO* connectedness of each market (19 countries) on frequency bands. This figure shows the *TO* connectedness dynamics of each market (19 countries) with the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents connectedness value. The thick black line indicates the total *TO* connectedness defined by Diebold and Yilmaz (2012). The thin black line (high-frequency) and the black dotted line (low-frequency) represent the frequency *TO* connectedness defined by Barunik and Křehlík (2018). The vertical grey dotted line represents the starting date of the sample studied in the article.

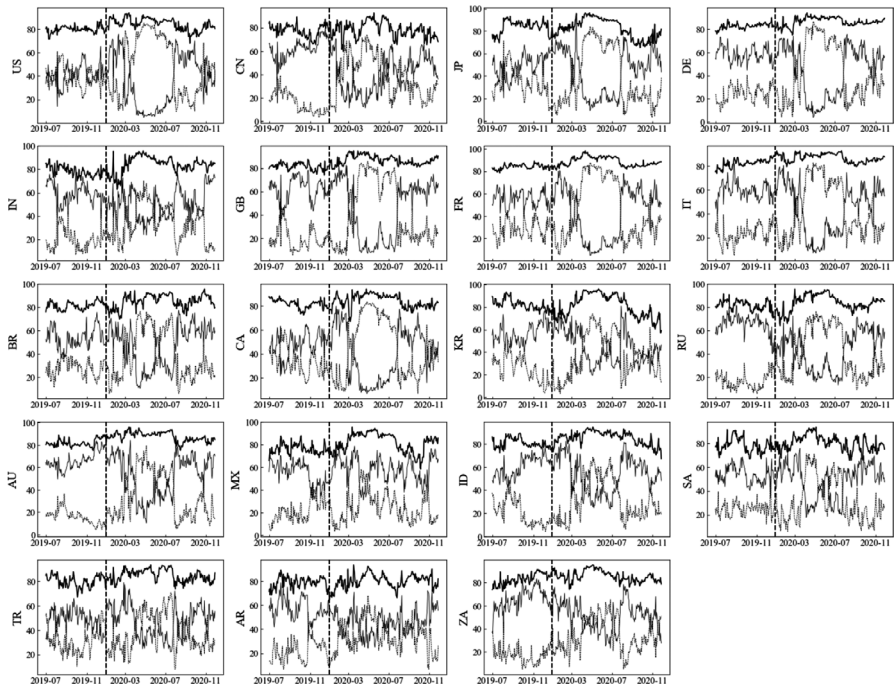


Figure A8 Dynamic *FROM* connectedness of each market (19 countries) on frequency bands. This figure shows the *FROM* connectedness dynamics of each market (19 countries) with the sample interval from 1 July 2019 to 30 November 2020. The horizontal axis represents time, and the vertical axis represents connectedness value. The thick black line indicates the total *FROM* connectedness defined by Diebold and Yilmaz (2012). The thin black line (high-frequency) and the black dotted line (low-frequency) represent the frequency *FROM* connectedness defined by Baruník and Křehlík (2018). The vertical grey dotted line represents the starting date of the sample studied in the article.